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Out of the darkness:
Re-allocation of confiscated real estate mafia assets

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Abstract

In an effort to tackle criminal groups, the Italian State allows the confiscation of properties belonging to individuals convicted for mafia-related crimes, and their re- allocation to a new use. This policy is considered both as an anti-mafia measure and as a way to partially compensate the society for the harm made by the criminal organisations. Whether and how this measure have had an impact on the local areas where it is implemented, however, has not yet been investigated. We test the hypothesis that the policy contributes to the regeneration of urban spaces by assessing its impact on the value of buildings in the vicinity of confiscated/re-allocated properties. To this aim, we perform difference-in-differences analyses, both at the level of local housing markets and at the level of individual buildings, investigating the externalities of the policy across the whole Italian territory. The results unveil a positive and significant effect of re-allocations of confiscated real estate assets on house prices, declining with distance from the re-allocation site. The impact is larger in cities with stronger mafia presence and in more deprived neighbourhoods. This suggests that the policy contributes to add value to the territory where it is applied and favours processes of urban revitalisation. These findings have important implications for the development of deprived urban areas characterised by a strong presence of criminal organisations.

Keywords: Organised crime, real estate confiscation, hedonic analysis, urban renewal policy, Italy.
JEL classification: K42, H23, R32, I24.

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2.1 Introduction

Urban areas are often characterised by pockets of poverty, crime, and marginalisation (Rosenthal & Ross, 2015). In light of that, addressing urban deprivation by means of effective regeneration measures represents a key challenge for policymakers (Bailey & Robertson, 1997). In particular, crucial objectives for interventions aimed at fostering the overall quality of cities - especially in underprivileged neighbourhoods - include tackling criminal activities and improving public spaces and housing (Atkinson & Helms, 2007; Koster & van Ommeren, 2019). Yet, evidence on the effectiveness of urban renewal policies of this kind is very limited.

This paper focuses on a large-scale, nationwide policy intended to reach the double goal of opposing organised crime and also contributing to the revitalisation of local urban areas. The Italian law allows to seize any real estate asset previously owned by organised crime members or affiliates and, through re-allocations, re-assign these assets to local communities by converting them into public housing amenities (e.g. centres for disadvantaged groups, green spaces, police stations). The intention of re-allocations, as conceived by the Italian legislator, is to contribute to the development and revitalisation of local areas in which they are made. As such, this measure not only acts as a crucial device for the appropriation of relevant resources from criminal activities, but also allows its redistribution to local communities. In this way, it contributes to eradicate criminal organisations in the areas where they are most rooted and prevent their spreading in territories selected by criminal groups for investment and money laundering, while also providing new opportunities and facilities to the residents of neighbourhoods plagued by the mafia. The buildings re-assigned to the citizenry, in their new role, should stimulate the development of a 'culture of legality', favour local entrepreneurship, and help recovering disadvantaged people from their conditions (Falcone et al., 2016).

While some descriptive and anecdotal evidence exists on the use and application of the policy (Camera dei Deputati, 2009; 2018; Transcrime, 2013; Falcone et al., 2016), this evidence tells little on its actual effectiveness. When confiscated assets are discussed in the media, the monetary value of the assets is systematically presented (e.g. Repubblica 2019), but other local effects - let alone overall capitalisation effects - are seldom considered. In spite of the fact that policies to

recover organised crime assets are widely diffused in several countries across the world[1], the re-allocation measure adopted by the Italian State has thus far been ignored by the academic literature. Whether and how real estate asset confiscations and re-allocations have had an impact on the wider society has not yet been investigated.

In this paper, we aim to fill this gap and investigate whether the re-allocation of confiscated mafia real estate assets produces any external effects on the local territory where such initiative takes place. Following the literature evaluating the impact of urban renewal policies, we capture the spillover effects of the intervention by looking at how the monetary value of buildings in the surrounding of confiscated and re-allocated assets responds to the implementation of the policy. The evidence produced by previous studies assessing the external effects of regeneration policy measures is mixed. While some works reveal that localised investments to revitalise urban areas have converted into higher house prices of neighbouring buildings (Santiago, Galster, & Tatian, 2001; Schwartz et al., 2006; Rossi-Hansberg, Sarte, & Owens, 2010; Ooi and Le, 2013; Koster & van Ommeren, 2019), others find that they have no effect on the property value of surrounding areas (Lee et al., 1999; Ahlfeldt et al., 2017). It is worth noticing that almost all these studies focus on specific neighbourhood of single cities where the programme has been implemented, producing hardly generalizable findings[2]. In contrast to that approach, we perform our analysis on the entire Italian territory, thus focusing on a very large and highly heterogeneous context. Hence, the main contribution of our work relates to the peculiarity of the intervention we examine, aiming to improve neighbourhoods by both increasing the stock of amenities and by tackling organised crime, as well as to the size and the spatial scale of the policy initiative.

Furthermore, our analysis is based on a unique database which allows to better identify the policy's impact. We exploit detailed information on the exact location and timing of over 15,000 confiscated and re-allocated properties in Italy and investigate their spillover effect in two ways adopting difference-in-differences empirical settings. First, we develop a panel model estimating how micro-aggregated local housing markets across the entire Italian territory respond to real estate asset confiscation and re-allocation. Second, exploiting information on over 60,000 geo-localised house sale points in the 55 major Italian cities, we provide a close examination of the

[1] According to the Asset Recovery Office of the European Commission, organised crime assets worth over 4 billion euros have been recovered in Europe alone in 2014 (the last year for which data is available) (ARO, 2014). Of this amount, over 1.6 bn was recovered in Italy.
[2] The only exception if the recent contribution by Koster and van Ommeren (2019), estimating the external benefits of a programme improving the quality of public housing in 83 deprived neighbourhoods throughout the Netherlands.

impact of re-allocations on the housing value of neighbouring buildings, as well as a detailed investigation of the spatial decay of the estimated effect. These two empirical strategies complement each other. The first covers the whole of the Italian territory, focuses on a longer time period (2005-2016) but is relatively less geographically accurate, given that it is based on local area data. The second presents a more limited temporal span (2011-2017) but the precision and accuracy of the analysis are higher due to the use of georeferenced real estate data as units of observation, and to the possibility of accounting for a very large set of buildings characteristics as controls. This setting allows to minimise any issue of selection by local area/building characteristics, as well as to control for any potentially confounding housing market dynamics. In addition, detailed information on confiscated/re-allocated assets make it possible to separately identify the two aspects of the policy (i.e. the confiscation and the re-allocation).

The results reveal strong and robust evidence of an external effect of re-allocations on neighbouring properties, noticeably increasing their value following the conversion of confiscated buildings into new amenities. This finding, consistent across estimation methodologies, reveals that for every building re-allocated in a territory, surrounding properties increase their monetary value between 0.4% and 0.8%. Examining the temporal dynamics of the effect by means of an event study, we show that the impact materialises the year following the re-allocation. Additionally, we demonstrate that this effect decays with distance and becomes insignificant 350m from the re-allocated building. When sub-dividing our sample into mafia and non-mafia regions, we show that the effect is driven by mafia-rigged areas, where the majority of confiscations and re-allocations take place. Furthermore, the impact appears stronger in deprived neighbourhoods. This suggests that the legislator's intent to improve the quality of neighbourhoods where the mafia presence is more pronounced may be effective.

A number of channels may be driving the uncovered effect. On the one hand, property values are directly influenced by the stock of amenities of the kind of those chosen for the re-allocations. A higher provision of green spaces, cultural facilities, social engagement centres, and similar buildings are expected to positively affect the monetary value of the neighbourhood they are in (Gibbons & Machin, 2008; Gibbons et al., 2014). On the other hand, the confiscation/re-allocation policy can influence disamenities such as the level of violence and crime, whose reduction also increases property prices (Gibbons, 2004, Linden & Rockoff, 2008, Ihlanfeldt & Mayock, 2010). Other mechanisms which may be triggered by the policy have to do with housing market

dynamics, i.e. variations in the supply of real estate properties. An increase (decrease) in housing supply would reduce (increase) house prices (Glaeser et al., 2005; Caldera & Johansson, 2013).

Our research, in addition to contributing to the literature on urban renewal policy evaluation, adds up to the growing studies on organised crime (e.g. Acemoglu et al., 2013; Barone & Narciso, 2015; Pinotti, 2015; Alesina et al., 2018; Di Cataldo & Mastrorocco, 2018; Pinotti & Stanig, 2018) and, more specifically, to the recently developing literature studying the societal implications of public initiatives against criminal organisations. The most widely analysed policy is the Italian law allowing the dissolution of local governments upon clear evidence of links between mafia clans and local public officials. Acconcia et al. (2014) exploit the temporary contraction in public investment occurring in post-dissolution periods to obtain estimates of the fiscal multiplier for Italian provinces. Daniele and Geys (2015) and Galletta (2017) demonstrate that dissolutions affect the quality of elected politicians and the proportion of public investments in neighbouring municipalities. Another examined policy is the accomplice-witnesses regulation. Acconcia et al. (2009) show the policy to be more effective the less efficient the prosecution system and the higher the internal cohesion of mafia organisations, while Garoupa (2007) analyses the policy within a principal-agent theoretical environment. No study has yet looked at confiscations and re-allocations of mafia real estate assets as we do in our paper.

The remainder of the paper is organised as follows. Section 2.2 describes the legislative measures we aim to evaluate, providing some key descriptive statistics. Section 2.3 presents our data. Section 2.4 introduces our empirical strategy at local housing market (OMI zone) and sale-point (micro) levels. Section 2.5 presents our findings. Section 2.6 concludes.

2.2 Institutional background: confiscation and re-allocation of mafia assets

The rise in mafia activities throughout the 1980s and a series of violent attacks led the Italian government to introduce a set of tougher anti-mafia measures. On 13 September 1982, in the aftermath of the murders of politician Pio La Torre and anti-mafia prefect Carlo Alberto Dalla Chiesa in Palermo, the national Parliament approved the 'Rognoni-La Torre' law (646/82), which represented a turning point in the fight against organised crime. This bill introduced two key measures fighting mafia activities, namely the inclusion in the Penal Code of membership of a mafia-type criminal organisation as a crime independent of other criminal acts (so-called 416-bis article), and the possibility for the courts to confiscate any asset belonging to members of the criminal associations, as well as to relatives, partners and other subjects who in the previous five

years played a cover-up role for criminal organisations. Any individual condemned with article 416-bis would immediately get their assets seized. The seizure may be converted into confiscation by the judges. To make law enforcement quick and effective, the law granted the judiciary full access to bank records in order to follow money trails.

The 'Rognoni-La Torre' law (646/1982) prescribes four steps to obtain the final confiscation:

1. The properties of suspects of belonging to mafia groups are scrutinised by the competent tribunal;
2. The seizure is decided upon by a panel of 3 judges. The asset goes under judiciary administration;
3. The judges provide a motivation for confiscation. The asset goes under first degree confiscation;
4. If appealed, the confiscation decision is reviewed by the Court of Appeal. The order can be 'revocation'[3] or confirmation (second degree confiscation).

The possibility of confiscating mafia-related goods and properties represents an extremely powerful tool in the hands of the Italian State in its fight against criminal organisations. Real estate asset confiscation is nowadays recognised as a fundamental instrument contributing to eradicate the pervasive presence of the mafia in the areas where it is most deeply rooted (Dalla Chiesa et al., 2016; Falcone et al., 2016). This is because real estate properties have a strong symbolic meaning for criminal groups. They are a physical representation of their power on the local territory and are often chosen by mafia families for their meetings. In addition, considering the large share of liquidity laundered by mafia groups into real estate properties - more than 50% of illegal mafia profits are reinvested into the legal economy, with real estate as one of the preferred sectors of investment (Transcrime, 2015) - the confiscation policy is a way to harm their business model and earnings.

A fundamental step in the management procedure of seized assets is their re-allocation to a new use by 'returning them to the citizenry' (Frigerio & Pati, 2007). This is operated by the Italian State, after the confiscation has been completed. The procedure of re-allocation, already introduced in the 646/82 law, has been regulated more clearly in 1996, when law 109/96 has been promulgated.

[3] Of all the confiscated buildings, only 14 have been 'revoked'. This suggests that judge bribing, even if taking place, is ineffective and plays little role as a confounder of our analysis

As can be seen in Figure 2. 1, the number of re-allocations has increased drastically in the aftermath of the approval of the 1996 law, and the large majority of re-allocations have occurred in the last few years.

Figure 2. 2 illustrates the geographical location of re-allocated properties across the Italian national territory. The confiscated and re-allocated mafia assets seem to be concentrated in metropolitan urban areas. Clusters can be observed in cities such as Milan, Rome, Naples, Reggio-Calabria and Palermo. A concentration of assets also seems to emerge in Southern Italian cities, with fewer clusters in Northern cities and even less in the central regions of Italy. The regions of Sicily, Puglia, Calabria and Campania also present higher concentrations of confiscated assets, which comes as no surprise given the publicised presence of mafia in these regions.

The approval of the 1996 law on re-allocation was the result of lobbying activity from the anti-mafia association *Libera*, asking for a faster management of confiscated assets and the possibility to use re-allocated goods for social purposes. As a result of that, the law lists a whole set of different uses for the re-allocated assets. The two broader categories are: 'social use' and 'institutional, justice and public order' (Figure 2. 3). The former category includes conversions of buildings into: anti-mafia/non-for-profit associations, senior centres, under18 centres, disable centres, health care centres, sport centres, green spaces. The latter includes: tribunal, police station, centre for migrants, archive, council houses. The logic of the policy is to use re-allocated assets to establish the principle of legality precisely where the control of the mafia is most entrenched, for example with the creation of police stations. Alternatively, buildings re-allocated for social use (e.g. by creating centres for employment-seekers) may contribute to provide concrete alternatives for individuals potentially attracted by organised crime. In all cases, the main principle behind this measure is the possibility for re-allocated assets to contribute to the regeneration of a local area and/or to become a fundamental resource in the fight against criminal organisations.

2.2.1 Local areas of confiscation/re-allocation

By exploiting 2011 Census data, it is possible to descriptively examine the characteristics of the areas where confiscated and re-allocated buildings are located. In order to do that, we construct a dataset at the level of Census areas for the entire Italian territory and focus on micro-areas with 100 or more inhabitants. For each of them, we are able to say whether there have been confiscations/re-allocations. We subsequently test for the correlation between a treatment

dummy (taking value 1 if in a given Census area there has been at least one episode of confiscation and re-allocation, and 0 otherwise) and a number of Census characteristics. The results of this test are reported in Table A2. 4 in the Appendix. As visible in the table, territories where the policy has been applied are relatively smaller in size, as shown by the negative association between the treatment dummy and the log population variable, and they have a higher proportion of unemployed people, of families renting their house, and buildings in bad conditions. All in all, this evidence seems to suggest that, as hypothesised, the policy is most often being implemented in underprivileged territories[4]. Crucially, when we replicate the empirical test with the inclusion of local housing market fixed effects (OMI FE), it can be noted that none of the Census variables returns a significant coefficient, indicating that area characteristics are balanced in this case.

2.2.2 Re-allocation timing

The implementation of law 109/96 and the creation in 2010 of a National Authority for Mafia-Confiscated Assets (hereafter ANBSC) has contributed to speed up the application of the law, progressively increasing the number of confiscated real estate assets being re-allocated. Yet, the average time between confiscation and re-allocation has been of over 8 years even after 1996, with only 83 properties in total being re-allocated in the same year or the year following the confiscation, as visible in Table A2. 1. The average length of the re-allocation procedure is sharply varying across the national territory, as illustrated in Figure A2. 1 in the Appendix, with no clear identifiable geographical pattern. Table A2. 3, reporting the count and share of re-allocations by political colour of local governments over the 1998-2017 period, suggests that the length of the re-allocation procedures is unrelated with the political colour of the municipal government where the asset is located. The proportion of buildings taking either less than 10 years or 10 years or more to re-allocate is almost the same for each government type[5].

Next, we examine how the length of re-allocation procedure correlates with the characteristics of local areas and the type of building being assigned to a new use. Table A2. 4 reports the results of an exercise testing for the correlation between the duration of re-allocation procedures, computed as the difference between the year of re-allocation and the year of confiscation, and a

[4] In Italy, approximately 72% of the houses are owned by residents. As a result, being rented is often a condition of more disadvantaged families balanced in this case.

[5] Comparing column (4) with column (2) of Table A2. 3, it also appears that re-allocations occur less than proportionally under governments run by civic lists - i.e. politicians with no clear ideological affiliation - than in governments ruled by left-wing, right-wing, or centre governments. As a consequence, it appears important to account for the political colour of the local governments in our analysis, which we do as we control for any municipality time-varying characteristics by means of municipality-year fixed effects.

number of variables measured either at the Census level or at the level of re-allocated building. The correlation between these variables and the length of re-allocations is estimated first by accounting for re-allocation year fixed effects, then including local housing market (OMI) fixed effects. Table A2. 4 illustrates that re-allocations tend to take longer in territories with higher unemployment, i.e. in more deprived territories where it may be presumed that courts are relatively less efficient. However, as fixed effects are included in the model, none of the local characteristics emerges as significantly associated with the policy implementation timing. Furthermore, re-allocations take generally longer for buildings assigned to institutional use, while they take less time for buildings assigned to social use. Again, this correlation disappears with the inclusion of fixed effects in the model[6].

2.2.3 Heterogeneity of re-allocated assets and policy impact

Mafia organisations generally own both operational and economic assets. The former are critical resources to exercise sovereignty over their market, whereas the latter are investments and money laundering machines. Operational assets such as real estate properties serve both as inputs for the illicit activities, insurance system against detection for the family of the members of the organisation and institutional signals for the entire community. The different role played by these assets suggests to differentiate between different regions where they are located. Another important source of heterogeneity is linked to the different types of re-allocation.

The policy's impact can materialise in various ways. First, the confiscation/re-allocation may be weakening criminal organisations. Asset seizure and confiscation might have a direct effect on the mafia's economic power, and act as a deterrent reducing *ex ante* its size[7]. In addition, the policy might be particularly effective when complemented with plea-bargaining and other forms of amnesty for the agents, since it counterbalances the potential savings in labour cost for the organisation, with a higher punishment in case of detection for the employer. Decreasing the welfare of individuals linked by strong ties to the mafia could constitute a relevant deterrent even in absence of detection. Moreover, the simple confiscation could have *per se* an effect on the perception of impunity that often characterise criminal organisations. A weaker presence of

6 This exercise has been reproduced also by including fixed effects for local Court instead of OMI fixed effects, obtaining very similar results.

7 This second dynamic is consistent with the model proposed by Garoupa (2007), where a higher punishment for the employer fosters a decrease in the number of agents and in information diffusion.

criminal groups is expected to materialise into a higher value of buildings in the area where confiscations take place (Gibbons 2004, Linden & Rockoff 2008, Ihlanfeldt & Mayock 2010).

Second, the re-allocation measure could serve as an extraordinary engagement device for the local community (Falcone et al., 2016). Non-profit organisations could use assets located in critical areas to organise bottom-up initiatives and sustain institutional change. This process may contribute to the revitalisation of the targeted areas also through the attraction of competitive firms and skilled workers (Storper & Venables, 2004). All this would capitalise into higher house prices in the neighbourhood area.

Third, the involvement of local authorities in the decision process regarding the allocation of the real estate asset could counterbalance the influence exerted by the criminal organisation. A corrupted politician might selfishly decide to support the fight against the organisation, in order to obtain political support thanks to the provision of a new public asset.
All these sources of heterogeneity are investigated in section 2.4.3.

2.3 Data

The empirical analysis relies on a novel dataset constructed from a wide range of sources. First, data on confiscated and re-allocated real estate assets have been extracted from the National Agency for the Administration and Destination of Seized and Confiscated Assets from Organised Crime (ANBSC). This includes detailed information on all the 15,698 re-allocated buildings on the whole Italian territory with their full address, the date of confiscation and re-allocation, the type of building and of re-allocation, the local court responsible for completing the procedure, the administrative entity responsible to manage the building once re-allocated. Each asset has been correctly geolocalised. Of these buildings, a relatively small portion is sold on the housing market (746) or demolished (2). These assets are dropped from our sample.

In the first part of our analysis, we use housing transaction data at a micro-aggregated zone level (Osservatorio del Mercato Immobiliare, or OMI), a spatial division of the Italian territory defined by the Italian Revenue Agency. OMI zones are smaller than neighbourhoods and correspond to functional local housing markets, i.e. homogeneous real estate markets for similar property types[8].

[8] According to the National Real Estate Agency, OMI areas are defined as: '*a continuous portion of the municipal area that reflects a homogeneous section of the local real estate market, where there are uniform prices for similar economic and socio-environmental conditions. This uniformity is translated into homogeneity in the positional, urban, historical-environmental, socio-economic characteristics of the settlements, as well as in the provision of services and urban*

The dataset spans from 2006 to 2016. For each OMI zone of Italy and for each real estate asset typology, the dataset includes maximum and minimum selling prices of properties. Following (Manzoli et al.), we compute simple averages between the minimum and the maximum price for each OMI zone – asset type. The values, computed for each quarter, are subsequently averaged at the year level. Within each OMI, the square deviation is usually lower than 1.5. OMI areas are drawn at the infra-municipality level, based on similar socio-economic and urban characteristics, building infrastructures and quality. All these features are crucial to determine prices[9] (Budiakivska & Casolaro, 2018).

We decide not to exploit all the information of the OMI dataset and to consider the value of prices only for the most representative categories, i.e. civil properties in normal state of conservation which are usually private residential buildings (excluding chalet, villas and boxes). We retain over 38,000 OMI zones per year from 2005 to 2016, 1718 of which have had at least one episode of re-allocation over the analysed period. Figure 2. 4 zooms into three major Italian cities, Milan, Naples, and Rome, to show their OMI zones and re-allocations.

The second part of our analysis exploits 53,728 geo-localised house sale points, spanning from 2011 to 2017 and collected from Immobiliare.it, the biggest Italian real estate website. These data are based on real estate properties sold in the 55 major Italian cities[10], with homogeneous coverage of the website across different cities as shown in Figure 2. 5. The dataset does not provide actual selling prices but asking prices that we use as proxies for the actual transaction prices[11]. The files have been then compiled, cleaned and checked for duplicates through the website unique identifier for each ad[12]. Finally, some of the missing values were filled by using the textual description of the ads. A recent paper by Loberto et al. (2018) which focuses on the comparison between Immobiliare.it data and OMI data provided by the real estate market

infrastructure'. In each OMI zone, the lowest unitary market value recorded for each building type should not be lower than 50% of the value recorded the most expensive asset in the same category.

9 The prices reported in the OMI dataset are obtained from various sources, principally the analysis of actual prices specified in administrative archives or quoted by market operators. In cases of missing observations, the data is integrated with assessments of local experts aimed at correcting imperfections or attributing a reference price whenever the low number of transactions limits the representativeness of the reported values.

10 These are: Alessandria, Ancona, Aosta, ,Ascoli Piceno, Bari, Bergamo, Bologna, Bolzano, Brescia, Cagliari, Campobasso, Caserta, Catania, Catanzaro, Cosenza, Firenze, Foggia, Genova, Isernia, La Spezia, L'Aquila, Latina, Livorno, Matera, Messina, Milano, Modena, Monza, Napoli, Novara, Nuoro, Padova, Palermo, Parma, Perugia, Pesaro, Pescara, Pordenone, Potenza, Prato, Reggio di Calabria, Roma, Salerno, Sassari, Savona, Taranto, Teramo, Terni, Torino, Trento, Trieste, Udine, Venezia, Verona, Viterbo.

11 Following Loberto et al. (2018), we assume that the removal of the ad corresponds to the sale of the property

12 When a change of price was tracked, the final most conservative price was recorded.

observatory of the Italian Tax Office, found the Immobiliare.it data provides an appropriate picture of the Italian housing market, consistent with official sources.

The micro-level dataset includes a wide range of structural attributes including floor space (m2), building height, type of property (studio, apartment, house, villa), the number bedrooms and bathrooms, floor, the date of construction, garage or parking facility and the type of heating an energy consumption.

In addition, a long list of controls is collected from the Italian census (2011), the Italian National Geoportal of the Environment, the Real Estate Observatory of the *Agenzia del Territorio* (AT), the Ministry of Education and Open Street Map. These include a series of controls for pre-existing amenities (i.e. already in place before re-allocations) such as typology of buildings on the street of the asset, distance to a range of natural and commercial amenities, distance to parking and transport controls, as well as the locations of schools (see Table A2. 5). Labour market, education, real estate quality and demographic data collected for the 2011 Italian Census were also obtained from the Italian Institute of Statistics (ISTAT). Descriptive statistics for treatment and control variables are reported in the Appendix (Table A2. 6, A2.7, and A2.8).

2.4 Empirical Strategy

In order to correctly estimate the effect of the confiscation and re-allocation of Mafia assets, we develop two complementary empirical strategies. First, we focus on the longitudinal trends of local homogeneous housing markets (OMI), exploiting the 2005-2016 time period and considering the entire Italian territory. This difference-in-differences strategy allows us to first test for a significant policy effect on micro-aggregated local housing markets. Next, we perform our analysis at the level of sale point, further testing for the spillover effect of the policy on house prices, capturing the spatial decay of the estimated effect and investigating the heterogeneous treatment effect. This hedonic pricing model is estimated as a repeated cross-sectional difference-in-differences.

2.4.1 OMI areas

First, we analyse the effect of confiscation/re-allocation policies on property prices aggregated at the OMI area level. Average values are computed starting from the minimum and maximum market values per zone to obtain average euro/m^2 house prices.

In order to test for the effect of confiscation and re-allocation of real estate assets on house prices, we rely on a differences-in-differences panel model accounting for the timing of confiscation and re-allocation of one or more properties in each OMI zone.

The estimated model is as follows:

$$lnp_{jt} = \alpha C_{jt} + \beta R_{jt} + \sum_{k=1}^{n} \gamma_k X_{jkt} + \delta_j + \lambda_t + e_{jt} \quad (1)$$

Where lnp_{jt}, the natural logarithm of average housing prices per square meter in OMI *j* and year *t,* is a function of a different set of variables. The two key variables in the model are the treatment variable C_{jt}, switching on for OMI *j* in the year(s) when confiscation(s) took place, until the moment of the re-allocation, and the treatment variable R_{jt} switching on from the moment in which a confiscated property has been re-assigned to a new use until the end of the sample period. As per our hypotheses, we expect a general increase in house prices in 'treated' OMI areas during the post-re-allocation period. This model captures the extensive margin effect of confiscations/re-allocations.

To control for different sources of heterogeneity in the sample, we exploit time-variant variables (X_{jkt}) retrieved from the 2011 Italian Census. We control for the number of properties in each area, the status of the buildings and other socio-economic conditions of the household living there (unemployment, level of education). In all specifications, we include time (λ_t) and OMI (δ_j) fixed effects. Year dummies allow to control for significant sudden generalised shocks in the Italian housing market, while OMI dummies account for any time-invariant factors at the level of local housing markets[13]. Furthermore, standard errors are clustered at the level of municipality, so to correct for the presence of spatial autocorrelation. The model is estimated for the 2005-2016 period.

In order to isolate the effect of confiscations and re-allocations, we focus exclusively on OMI zones having experienced only *one* episode of confiscation(s) or re-allocation(s) in time. That is, we exclude all OMI zones where confiscations and re-allocations have occurred over multiple years. The single episodes of treatment we consider may involve more than one single building confiscated/re-allocated if the confiscations/re-allocations of buildings in that OMI area have

[13] Adopting OMI zones as our unit of analysis allows to minimise unobserved heterogeneity potentially confounding our estimates, given that these geographical units correspond to functional local housing markets.

been established all in the same moment. To minimise the effects of confiscations on re-allocations, we test our findings by excluding all OMI zones where the re-allocation took less than 10 years to be completed.

2.4.2 Sale-point analysis

In our main specification, we estimate a hedonic pricing model using micro geo-localised data at the level of sold building. Although this is considered the ideal approach in the hedonic literature, few studies have used this strategy to explore the impact of public policies as punctually localised as the one under consideration in this paper. Moreover, our dataset is novel in terms of size and spatial detail for the Italian territory. In line with other policy evaluations (e.g. Ahlfeldt et al., 2017), our first assumption lies in expecting a very localised effect of confiscated assets on surrounding real estates.

Using geographic information system (GIS), we begin by drawing perimeters up to 500m radii around each of the re-allocated assets. These buffers roughly correspond to an average 5 minutes walking distance from the real estate asset, spatially translating the expected local effect (EVSTUDIO, 2016; Gibbons & Machin, 2008). The buffers of 500m represent the maximum extent to which we expect to measure a local effect. Given the punctuality of the policy, we in fact expect externalities to be more localised, with radii varying between 100m to 500m from confiscated/re-allocated assets[14].

Figure 2. 7 provides an illustration of our approach. All sale points with no assets in the buffer zone act as controls, while sale points located in the same OMI area, with at least one confiscated asset within their buffer radius act as treated units. We drop from the sample any observation with no confiscated asset within 2km distance, excluding in this way the large majority of OMI areas with no treated units. Exploiting information on each building's sale date, we can exploit the timing of the re-allocation and identify the impact of the policy on the prices of buildings inside the buffer and being sold *after* the re-allocation took place. This method allows us a highly accurate focus on the neighbourhood of the confiscated and re-allocated asset, identifying with precision the treatment area.

[14] In choosing our buffer radii we follow the literature on the evaluation of the spillover effects of urban renewal policies (i.a. Linden & Rockoff 2008; Schwartz et al., 2006; Rossi-Hansberg et al., 2010; Ahlfeldt et al., 2017)

To compute the external impact of the confiscated and re-allocated real estate assets we estimate the following hedonic pricing model:

$$\ln p_{ijmt} = \beta_1 C_{i,t-n}(d) + \beta_1 R_{i,t-n}(d) + \beta_3 C_{i,t+n}(d) + \beta_4 R_{i,t+n}(d) + \rho X_i + \delta_j + \theta_{mt} + e_{ijmt} \quad (2)$$

where $\ln p_{ijmt}$ is the natural logarithm of house price per m2 of real estate property *i* in OMI zone *j*, municipality *m*, sold in year *t*. $C_{i,t-n}$ is a treatment indicator, defined as number of buildings confiscated within a radius *d* from building *i* in year *t-n* (n=1,2,3) before it was sold. Similarly, $R_{i,t-n}$ is a treatment indicator defined as the number of buildings re-allocated within distance *d* from building *i* in year *t-n*. The two treatment variables capture the intensive margin effect of confiscations and re-allocations on house prices of neighbouring buildings.

The variables $C_{i,t+n}$ and $R_{i,t+n}$ (n=0,1) are post-treatment covariates, that allow us to account for pre-treatment differences in housing prices. X_i is a vector of structural and amenity controls of property *i*, the latter which were constructed from multiple geographical datasets for all the Italian territory and e_{ijmt} is the error term for property *i*. We compute distances to a large range of amenities as specified in the data section (including distance to city CBD) to account for omitted variable bias. We also control for socio-economic conditions by census tract from the 2011 Italian Census. Although our temporal dimension is shorter than for our OMI analysis, we control for local time-invariant factors and for common shocks, adopting OMI zone (δ_j) and municipality-year (θ_{mt}) fixed effects. The model is estimated for the 2011-2019 period, for every distance *d* = {50, 100, 150, 200, 250, 300, 350, 400, 450, 500}. Standard errors are clustered at the OMI zone level so to correct for the presence of spatial autocorrelation.

This research design allows to separate the effect on property values of confiscation or re-assignment of real estate assets from correlated location effects (Koster et al., 2012; Noonan & Krupka, 2011).

2.4.3 Estimation issues

In order to correctly identify the effect of confiscation/re-allocations on housing prices, a number of estimation issues need to be addressed.

First, we need to consider potential problems of selection. According to Transcrime (2017), mafia organisations tend to invest more often in territories they control. If housing prices in these areas

have peculiar trends for reasons not associated with the analysed policy, our results may be biased.

Second, the application of the policy may depend on the quality of public institutions. In areas where public authorities are more likely to be captured by criminal organisations through bribes and/or where the re-allocation procedure takes more time to be completed, we expect a lower density of seized (and re-allocated) assets. Figure A2. 1 in the Appendix shows no clear geographical/regional pattern in relation to the efficiency of local courts responsible for re-allocations, suggesting that court efficiency is semi-random. Re-allocation procedures exhibit a high degree of heterogeneity, with no clear differences in the average duration between Northern and Southern Italian regions. However, Table A2. 3 shows some evidence that the duration of the re-allocation procedure may vary depending on the political colour of the local government administrating the municipality where the asset is located.

In order to deal with these issues, we include a number of controls in our models. To start with, we always include OMI zone fixed effects in the estimates. As mentioned above, OMI are micro-geographical areas, smaller than neighbourhoods, characterised by homogeneous real estate markets. Areas are revealed at the infra-municipality level, sharing similar socio-economic and urban characteristics, building infrastructures and quality, namely the features which are crucial to determine house prices (Budiakivska & Casolaro, 2018). In Table A2. 2, we exploit data retrieved from the 2011 Italian Census to test the balancing properties of our setting on a number of local area characteristics, finding no significant difference within OMI areas (when OMI fixed effects are controlled for), confirming the homogeneity of these geographical units.

As a further test for that, we also verify if OMI areas can be considered as homogeneous units for less 'tangible' characteristics such as social capital[15]. To study the endowment of social capital within OMI areas we follow Putnam's (1993) seminal contribution and more recent literature (Peri, 2004; Guiso et al., 2004; Buonanno et al., 2009) and exploit variation in voter turnout within OMI areas as a proxy for civic engagement. We are able to measure this variable at the level of polling station in the four largest Italian cities: Rome, Milan, Naples, and Palermo, which are also those with most confiscated and re-allocated assets (see Figure 2. 2). To minimise any distortion of electoral competition from organised crime (more common for elections held at the municipal

[15] Scholars sub-divide social capital into bridging and bonding, the former referring to linkages between different groups in society, while the latter referring to strong ties within the same groups. In Southern Italy, a lower level of bridging and an excess of bonding social capital has been connected with the activity of criminal organisations (Trigilia, 2001)

level) we focus on the 2009 European Elections[16]. Our assumption is that differences in voter turnout between treated polling areas and areas where no confiscation is recorded would undermine our claim of institutional homogeneity of neighbourhoods within OMI areas. The results shown in Table A2. 9 unveil a negative association between voter turnout and re-allocations, which however becomes insignificant when OMI fixed effects are accounted for, thus again confirming the homogeneity of OMI zones.

In addition to OMI fixed effects, our hedonic models control for Census area characteristics, further minimising any potential confounder within OMI areas. Moreover, the specifications account for generalised shocks in housing markets by means of year fixed effects, as well as for any municipality-specific characteristics varying over time with municipality-year fixed effects. The latter control allows to account for any change in the political composition of the local government potentially influencing the timing of the policy and its implementation. To conclude, the very large set of control variables at the level of building - including a number of variables identifying pre-existing amenities - further minimises the possibility that any observed policy effect is due to non-random characteristics of the local area where the policy is put in place.

Finally, we include in our model two pre-treatment variables, measuring the assets confiscated the same year of the transaction and the following year[17]. In this way, we test for pre-treatment differences in housing prices between treatment and control groups.

Another possible issue relates to the fact that our study focuses on a policy being implemented in two steps: first the confiscation, and then the re-allocation. In order to minimise any possible effect of confiscations on re-allocations, our analysis focuses on re-allocations taking ten years or more to be completed. The 'double' treatment may give rise to one additional concern, namely the fact that the confiscation affects other outcomes such as labour mobility. To minimise this issue, we test the impact of the policy within a very limited distance from the treatment site, as low as 150m, where the probability of any labour/firm relocation is unlikely to be more concentrated than in the outer ring.

16 European Elections are known to be hardly influenced by criminal organisations, due to the size of electoral constituencies (the Italian territory is divided in 5 macro-constituency). Moreover, in contrast to mayors and Municipality/regional councillors, Members of the European Parliament do not have the power to affect the allocation of funds at the local level.

17 According to Frigerio and Pati (2009) and Transcrime (2017), the large majority of assets become operative between 6 months and 18 months after the reallocation time. Fort this reason, we do not expect any treatment effects in the treatment year.

2.5 Results

2.5.1 OMI-level analysis

We begin by performing the analysis at the level of OMI areas, focusing on the whole Italian territory and relying on a panel dataset between 2005 and 2016. The OMI dataset includes information on house prices - our dependent variable - for a large variety of real estate properties. In order to obtain comparable observations and minimise heterogeneity, we perform our estimates by focusing on the monetary value of the most common type of property in Italy, i.e. civic houses , further restricting the analysis to those whose quality status is classified as 'normal' by the Italian land registry. While this strategy marginally reduces the number of OMI areas in the sample, it prevents differences in property prices to be driven by the diverse composition of buildings in a given area.

We restrict our analysis to OMI zones having experienced confiscation and/or re-allocation events only once over the full period of implementation of the policy (1982 to date). In other words, we exclude from the sample all local areas having experienced multiple episodes of confiscation/re-allocation. The results of the difference-in-differences analysis are reported in Table 2. 1.

We begin by testing the relationship between confiscation and property prices. The first specification in column (1) only includes the treatment variable accounting for whether an OMI zone has experienced a confiscation of one or more real estate assets at any point in time during 2005-2016. This variable switches on in the year of confiscation until the moment of the re-allocation. In column (2) we exclude all re-allocation years from the analysis. In both cases, the coefficient is not statistically significant, suggesting that house prices have not varied significantly in the aftermath of a confiscation episode.

Next, we test the effect of re-allocation on OMI zones house prices. In column (3) we include the treatment variable for re-allocation, switching on at the time of the re-allocation episode in the OMI zone. This specification considers all re-allocated buildings, regardless of the time it took to re-allocate them, while in column (4) we focus our attention only on re-allocation that took 10 or more years to be completed. Finally, in column (5) we include both treatment variables at the same time. It can be seen that in all cases the estimates return a positive and strongly significant coefficient, indicating that the selling price of houses within OMI areas in which the re-allocation

took place increased in the aftermath of the re-allocation. In our favourite specification, a reallocation of a single asset is associated with a 4.2% increase in property prices in the OMI area.

It must be noted that, as all the sold re-allocated buildings are dropped from our sample, these estimates are testing the effect of real estate assets which are appropriated and managed by public institutions (mainly municipalities). Therefore, the observed increase in value in the OMI zones is due to a higher price of the buildings in the same local housing market of the re-allocated one(s).

In Figure 2. 8 we examine the timing of the estimated re-allocation effect. We perform an event study (Angrist & Pishke, 2008) by including a full set of leads and lags dummy variables for the entire period before the treatment year and during the treatment, using the year before the re-allocation as reference category[18]. As before, the sample is restricted to OMI zones having experienced only one re-allocation in time. The figure reports the coefficients for each year pre/during treatment with 90% confidence intervals, providing further evidence on a positive and significant effect of the re-allocation event. In all years before the re-allocation, there is no significant difference in house prices between treated OMI zones (i.e. those in which real estate assets will be re-allocated) and other OMI zones, as all coefficients specifically referring to years prior to the re-allocation are not statistically different from zero. The significant difference in prices emerges in the following years, already visible in the first post-treatment year.

2.5.2 Sale-point analysis

Having shown some evidence of a significant re-allocation effect of the value of buildings surrounding those re-allocated, we further examine this relationship with micro-level data. Table 2. 2, A2.10, and A2.11 report the results for the hedonic analysis conducted at the sale point level, using different radii to define the treatment area.

Results for the model estimated at a distance threshold of 250m are reported in Table 2. 2. The first specification in column (1) includes structural controls and OMI/year fixed effects only. It can be seen that the estimate returns a positive and significant coefficient one and three years after the treatment kicks in. Results are consistent in column (2)-(4), where we progressively add

[18] While this implies including dummies up to 11 years before and during the treatment, the reliability of estimated coefficients reduces for years far away from the start of the treatment, as the number of observations for each year is inevitably lower.

building, pre-existing amenity and socio-economic controls. No significant difference between treatment and control groups are recorded in the treatment year and before. It must be noted that, as no information is available on the exact period of the year when each property is re-allocated, re-allocations in t_0 might happen prior to the housing sale event. As a result, it is not surprising to find no significant result at t_0, consistently with the event study in Figure 2. 8. Overall, the regression results suggest positive and lasting effect of the re-allocation policy.

In column (5) we extend the specification to include municipality-year FE, in order to control for city-level exogenous shocks. Doing that, we implicitly rule out any municipal-level treatment effect. While this strategy is expected not to affect results concerning the largest cities in our sample, medium-size urban areas might still record an overall benefit from the policy. Nevertheless, results appear consistent with previous estimates. The coefficient in column (5) is positive and significant in the year following the treatment and in the third year after the treatment. Once identified the time trend in the event study, we estimate the overall effect of the policy. Column (6) only includes a cumulative treatment proxy, corresponding to the sum of the neighbouring assets re-allocated over the 3-year period. Finally, in column (7) we include in our specification a similar proxy for confiscated assets. Once again, the estimates report a positive and significant coefficient for re-allocations, while insignificant for confiscations. Overall, the findings are consistent with the existence of a positive externality arising from the reallocation of confiscated assets. For each asset confiscated in the previous 3 years, neighbouring property prices are expected to rise by 0.4%. Although the results generally confirm the dynamic found in the OMI analysis for confiscation and re-allocation events, the magnitude is significantly lower. This difference is probably due to the specific features of the two empirical strategies. The OMI analysis focuses on OMI areas where only one confiscation/reallocation event took place. By contrast, the sale-point analysis allows for multiple treatment. The difference might be partially explained with decreasing returns of confiscated/reallocated assets. Moreover, the second strategy guarantees a more precise identification of the policy effect. Controlling for property observable characteristics and unobservable time-invariant area characteristics, we better identify the effect of the confiscation policy on the properties located in the immediate neighbourhood around the seized assets. Positive effects on property prices taking place beyond the distance threshold chosen are likely to determine a downward bias in our estimates.

Despite the fact that a proper cost-benefit analysis is beyond the scope of this study, it is possible to discuss the magnitude of the policy effect. To our knowledge, this is the first study to investigate

the impact of confiscation policies on property prices. As a result, it is not immediate benchmark to compare our results with. However, our result can be compared with studies analysing the effect of crime at a similar spatial scale. Thaler (1978) finds that a one standard deviation increase in the incidence of property crime reduces home values by about 3 percent. A more significant effect is reported by Gibbons (2004), that finds a standard deviation decrease in local density of criminal damage to be associated with a 10% price increase in the average Inner London property.

Our results can then be analysed in relation to studies investigating the effect of local amenities on property prices. Machin (2011) reviews 11 studies investigating the nexus between school quality and housing prices, finding a median change of 4% in housing prices following a standard deviation change in school quality. Similarly, the presence of sex offenders reduce property prices by 2-4% (Linden and Rockoff, 2008; Pope, 2008). On the other hand, changes in toxic emissions from industrial plants is associated with a 10% change in house price (Currie et al., 2015).

With respect to different amenities, our estimates appear to be significantly lower. However, the policy considered is likely to be significantly cheaper for local authorities. Moreover, the strategic position of confiscated assets, mostly located in deprived neighbourhood, is such that the policy is likely to particularly benefit deprived social groups.

In Table A2. 10 in the Appendix we report regression results for the hedonic micro-level model estimated within a radius of 150m, that we consider the minimum area of analysis, on the basis of our sample size and the related literature (e.g. Rossi-Hansberg et al., 2010). The basic specification in column (1) reports positive and significant coefficients for the third year following the treatment. The results are generally confirmed in magnitude and significance while adding to the specification the full set of housing sale level controls. While estimating the cumulative treatment in column (6) and (7), the treatment coefficient is higher than the one estimated with a 250m radius. Overall, at 150m distance, we again find evidence of a positive effect of the re-allocation policy.

This result, obtained with such a small distance from the treatment point, allows to further minimise any potential concern of endogeneity due to the presence of time-varying confounding factors at the OMI level. If, for instance, the confiscation has activated some dynamics we are not explicitly accounting for in the model (e.g. related to labour mobility), this may bias our estimates.

However, the likelihood that these dynamics are stronger within the 150 metres from the treatment sites than in the rest of the OMI area is extremely low.

In Table A2. 11 we investigate treatment effects at 500m radius. Columns (1) to (5) report results for our main specification. Overall, we find some evidence of a positive effects in the years after the treatment. The coefficients exhibit a lower magnitude with respects to the one estimated in the 250m distance specification. Consistently, the coefficient is lower than with other threshold distances when considering the cumulative treatment and non-significant. Conversely, we do find some evidence of a negative effect of confiscations on house prices.

In order to investigate the distance decay of the policy, in Figure 2. 9 we combine together the estimated coefficients from 100 to 500m, with relative confidence intervals, controlling for confiscation and all other set of controls and fixed effects. The Figure allows to appreciate the spatial decay characterising the cumulative treatment. The coefficients are monotonically decreasing, with a larger standard error up to 150m due to the lower sample size. Overall, the policy is found to have a positive and significant effect up to 350m. At a radius of 350m the policy still has a positive effect, but the declining coefficient suggest the transactions localised further than the 300m threshold to be less affected. At 400m distance the coefficient is still positive, but no longer significant.

In Table A2. 12 , we test the robustness of these results by including in the model a control for the buffer zone. If there are time-invariant characteristics which are specifically located at a 100m to 500m distance from the re-allocated real estate asset and have an influence on house prices, this would act as an omitted variable and bias our estimates. The specification including a buffer zone dummy variable is fully controlling for that. The inclusion of this control leaves the main results virtually unaltered, as the re-allocation retains significance and the magnitude of the coefficients is lower as we move away from the treatment point. Interestingly, the buffer zone dummy is statistically insignificant up until 300m from the re-allocated asset, suggesting no generalised difference in house prices in the treatment areas vis-à-vis the untreated area within OMI zones.

2.5.3 Where is the effect stronger?

To conclude our analysis, we further characterise the estimated external impact of re-allocations on the value of surrounding real estate buildings by testing *where* is this impact stronger.

To begin with, the results commented above suggest that the impact of re-allocations on property prices is larger the higher the number of re-allocations - i.e. in presence of a higher density of re-allocated buildings. Hence, we may expect that the policy would produce the larger impacts in areas where organised crime groups are more rooted and where they invest the most. While we cannot directly measure the presence of organised crime, their strongholds are well known. Campania, Calabria, Sicily and Puglia are the regions in which Italian criminal groups have their roots[19] (Transcrime, 2013). More generally, criminal groups tend to prosper in more deprived areas, where public institutions are often perceived as weak and distant, the provision of public services is sometimes deficient, and employment opportunities are lower.

To test this hypothesis, we exploit the geographical extension of our dataset. We sub-divide our sample into regions of high mafia intensity (Campania, Calabria, Puglia and Sicily) and all remaining regions. The results, shown in Table 2. 3, indicate that the effect we obtain appears to be driven by the regions where organised crime has a stronger presence. As shown in Figure 2. 2, these regions are also those where the majority of re-allocations have been made.

Finally, we estimate the model by focusing on specific areas, selected on the basis of their characteristics. In particular, we attempt capture the degree of urban deprivation by means of two indicators related to labour market conditions and real estate characteristics of the area. We begin by sub-dividing the sample among OMI with average recorded unemployment rate above and below the 75th percentile of the national distribution (Census data). As visible in

[19] While organised crime is spread across the entire Italian territory (and beyond), it still maintains its strongest presence in the areas where it was originally formed. According to Transcrime (2013), the Cosa Nostra (Sicily), 'Ndrangheta (Calabria), Camorra (Campania) and Sacra Corona Unita (Puglia) preserve their strongholds in their regions of origin. The cities in our sample belonging to the four regions of high mafia intensity are: Bari, Foggia, Taranto (Puglia); Napoli, Caserta, Salerno (Campania); Catanzaro, Cosenza, Reggio di Calabria (Calabria); Palermo, Messina, Catania (Sicily)

Table 2. 4, the effect of re-allocations on house prices only appears for areas with higher unemployment levels. Next, we sub-divide the sample according to the proportion of buildings classified as in 'bad' conditions, again relying on Census 2011 information. Once again, the estimated effect appears to be driven by the most deprived and disadvantaged neighbourhoods.

2.5.4 Channels

In this study, we presented evidence that confiscation and reallocation policies can be powerful tools to regenerate deprive neighbourhoods. However, we have not discussed what are the mechanisms driving the increase in housing prices. In part, the capitalisation of re-allocations into higher house prices of surrounding buildings may be due to a safer environment, 'cleaner' from the activity of criminal organisations. This kind of dynamic would be consistent with the fact that a stronger effect is visible in mafia-rigged regions, where the larger proportion of mafia investment into real estate are made (Transcrime, 2013). The effect we obtain may also be the result of the improved view of a previously more deprived and less attractive neighbourhood, thanks to the new amenities. This explanation is linked to the fact that the majority of re-allocations take place in local areas characterised by a high share of buildings in bad state, and that the effect of the policy is stronger in more disadvantaged areas.

In absence of detailed geocoded data, we are not able to investigate in depth the underlying channels. However, in this section we run a simple exercise that could provide at least some indications regarding the mechanisms that explain our results. We exploit 2013-2018 annual reports produced by the DIA, the Anti-Mafia Investigation Directorate, that provide very detailed information on the territories under the influence of mafia organisation in 5 Southern cities (Naples, Reggio Calabria, Palermo, Messina). In particular, the DIA maps the power exerted by each single mafia family on the territory. The data are updated every year and make it possible to follow the evolution of mafia presence in small neighbourhoods and even in single streets (see Figure 2. 11).

Thanks to these data, we have constructed a street-level panel dataset on organised crime presence in Naples (see Figure 2. 12). Exploiting DIA data, we estimate the following model:

$$Camorra_{st} = \alpha C_{st} + \beta R_{st} + \sigma_s + \lambda_t + \delta_{zt} + e_{st} \tag{3}$$

where $Camorra_{st}$ is the number of camorra families active in street s, year t, or a dummy for camorra activity, C_{st} is confiscation dummy and R_{st} is the treatment dummy. The confiscation variable switches on from the year of confiscation(s) taking place in street s to the year before the re-allocation, while the re-allocation variable switches on from the year of confiscation(s) taking place in street s to the year before the re-allocation. The specification includes time-invariant street-specific factors (σ_s), time shocks (λ_t) and OMI-year FE (δ_{zt}). Due to the high heterogeneity recorded in street-level data, we only focus on a 100/200 meters radius from each road.

This empirical strategy can be interpreted in two ways. The analysis of the effect of confiscation on Mafia presence could provide some evidence on the actual effectiveness of the State in eradicating criminal organisations. However, criminal organisation activities are likely to be affected by unobservable factors correlated with public enforcement.

On the other hand, assuming the timing of reallocation to be exogenous with respect to mafia activity on the territory, the re-allocation of mafia assets could be seen as a 'deterrent technology'[20]. The signal given to local communities by the re-allocation to a new use of an asset previously associated with the power of the organisation on the territory, as well as the new services provided by the asset itself, could both increase the costs associated with the control of the territory. Considering the strong assumptions required to claim causality in such a framework, we perform it as a descriptive exercise to test our predictions that part of the effect of the policy on property price is due to changes in organised crime behaviour.

In

[20] Due to the lack of detailed geocoded data on deterrent policies and crime activities, most papers in the literature only focus on measures of expenditure in each policy. Two relevant exceptions are Draca et al. (2011) and Bell et al. (2014).

Table 2. 5, we regress the number of family operating in one street over the cumulative re-allocation variable, using a 100 meters radius. In the baseline specification (column (1)), confiscation is found to have a positive effect on the number of families per road, whereas the opposite effect is found for re-allocation events. When OMI-year FE are included (column (2)), the confiscation event becomes insignificant, while the coefficient for re-allocations, although losing magnitude, remains negative and significant. In Column (3) we focus only on treated roads, exploiting variation over time in the treatment variable. Results are consistent with the previous specification. Overall, confiscation is found to have an ambiguous effect on the influence of mafia families on Naples roads, while a significant and negative effect is found for the re-allocation of former mafia assets. I columns (4)-(6) we estimate the same specification using a 200 meters radius. Results are confirmed, but the coefficient magnitudes for re-allocation significantly declines.

Results suggest that re-allocation policies could decrease mafia activity in the neighbourhood where the reallocation takes place. However, the number of family could be a poor proxy for the actual power of Mafia on a territory. In Table 2. 6 we run a similar exercise, but this time we use a simple dummy that takes value of 1 if mafia presence is recorded in the street and 0 otherwise. The previous results are generally confirmed. Confiscation has a positive or no effect on the presence of mafia, while a significant negative effect is found following the re-allocation of confiscated assets. In this case however, when we focus on treated roads only, we find a positive and significant effect of confiscation while the negative effect of re-allocation events become less significant.

This exercise, conducted on a single city, does not allow us to draw conclusions regarding the effect of this policy on mafia activity. However, it supports our hypothesis that at least part of the regeneration effect of the re-allocation policy is obtained with the eradication of the pervasive presence of the mafia in the treated areas. On the other hand, the positive effect of the confiscation event on Mafia presence could be explained with the clan wars that often follow the conviction of important members of the organisation.

2.6 Conclusions

In an effort to tackle criminal organisations, the Italian State allows for the possibility to seize and confiscate real estate properties previously belonging to mafia groups. Such policy, widely considered as one of the most crucial tools to undermine the power of organised crime in local areas, entails the re-allocation of confiscated assets to a new use, supposedly contributing to the revitalisation of the territory in which this policy intervention takes place.

This paper assesses the extent to which re-allocations contribute to such regeneration process by testing their external effects on the monetary value of properties in the surrounding areas. Our estimates, performed at different geographical units of analysis and making use of unique micro-level datasets, unveil a robust positive relationship between re-allocation cases and the property price of neighbouring buildings. The increase is equal to 0.5%-0.8% per each re-allocated building, lasting a minimum of three years following the re-allocation.

This finding suggests that, as hypothesised (and as expected by the Italian legislator), re-allocations lead to significant spillover effects that add value to the whole territory where they are implemented. Such effect is visible in the range of up to 350m from each episode of re-allocation. The impact is stronger in more deprived neighbourhoods and in regions characterised by a stronger presence of criminal organisations.

With the available data, we are not currently able to investigate to what extent the observed effect is due to the eradication of the presence of criminal organisations or to a simple amenity effect. However, the exercise conducted at the street level suggests that at least a part of the effect could be associated with a reduction of the depressive effect of mafia activity on local economy.

In all cases, what emerges with clarity from our study is that the policy of re-allocating real estate assets recovered from criminal organisations has the important effect of increasing the value of

local neighbourhoods where such buildings are located. The policy we have assessed is not explicitly characterised as 'place-based' in nature, in the sense that it is not specifically intended for poor neighbourhoods, but rather can be implemented in both more and less developed areas. Nevertheless, we have shown that its primary application has been in local areas characterised by high unemployment and more unattractive buildings. Furthermore, its effect is noticeably larger in cities where the presence of organised crime is stronger. Hence, this suggest that an effective and rapid implementation of the re-allocation policy may favour the revitalisation of urban areas at higher disadvantage where mafia groups hold the upper hand.

References

Acconcia, A. Giancarlo Corsetti, and Simonelli, S. (2014). Mafia and Public Spending: Evidence on the Fiscal Multiplier from a Quasi-Experiment. *American Economic Review* 104.7, 2185-2209.

Acconcia, A. and Patrick Rey (2009). Accomplice Witnesses, Organized Crime and Corruption: Theory and Evidence from Italy. *Scandinavian Journal of Economics* 116, pp. 1116-1159.

Acemoglu, D. James A. Robinson, and Rafael J. Santos (2013). The monopoly of violence: Evidence from Colombia. *Journal of the European Economic Association* 11, pp. 5-44.

Ahlfeldt, G.M., S. Redding, D. Sturm, N. Wolf (2015). The Economics of Density: Evidence From the Berlin Wall *Econometrica* 83, pp. 2127-2189.

Ahlfeldt, G.M., Wolfgang Maennig, and Felix J. Richter (2017). Urban renewal after the Berlin wall: A place-based policy evaluation. *Journal of Economic Geography* 17, pp. 129-156.

Ahlfeldt, G.M. and Nancy Holman. (2018). Distinctively Different: A New Approach to Valuing Architectural Amenities. *Economic Journal* 128, pp. 1-33.

Alesina, A., Salvatore Piccolo, and Paolo Pinotti. (2017) Organized Crime, Violence, and Politics. *Review of Economic Studies*.

Angrist, J. and Jorn-Steffen Pischke (2008). Mostly Harmless Econometrics: An Empiricist's Companion. *Princeton University Press*

Atkinson, R. and Gesa Helms (2007). Securing an urban renaissance: Crime, community, and British urban policy. *Policy Press*

Bailey, N. and Robertson, D. (1997). Housing renewal, urban policy and Gentrification. *Urban Studies*.

Barone, G. and Narciso, G. (2015). The effect of mafia on public transfers. *Journal of Urban Economics*.

Bell, B., Jaitman, L., & Machin, S. (2014). Crime deterrence: Evidence from the London 2011 riots. *The Economic Journal*, 124(576), 480-506.

Budiakivska, V. and Casolaro, V. (2018). Please in my back yard: the private and public benefits of a new tram line in Florence. *Temi di Discussione, Bank of Italy* 1161.

Buonanno, P. Daniel Montolio, and Paolo Vanin (2009). Does Social Capital Reduce Crime? *Journal of Law Economics* 52.1 , pp. 145-170.

Caldera, A. and Asa Johansson. (2013). The price responsiveness of housing supply in OECD countries. *Journal of Housing Economics* 22, pp. 231-249

Dalla Chiesa, Nando (2016). Il riuso sociale dei beni confiscati. Le criticità del modello lombardo. *Rivista di Studi e Ricerche sulla criminalità organizzata* 2.2: 15-25.

Daniele, G. and Benny Geys. (2015) Organised Crime, Institutions and Political Quality: Empirical Evidence from Italian Municipalities. *Economic Journal* 125, pp. F233-F255.

Di Cataldo, M. and Nicola Mastrorocco. (2018) Organised Crime, Captured Politicians and the Allocation of Public Resources. *SSRN Electronic Journal* 1556-5068.

Draca, M., Machin, S., & Witt, R. (2011). Panic on the streets of London: Police, crime, and the july 2005 terror attacks. *American Economic Review*, 101(5), 2157-81.

Falcone C.R., Giannone T. e Iandolo F. (2016). BeneItalia. Economia, welfare, cultura, etica: la generazione di valori nell'uso sociale dei beni confiscati alle mafie. *Edizioni Gruppo Abele*

Frigerio, L., and Pati, D. (2007). L'uso sociale dei beni confiscati–Programma di formazione sull'utilizzazione e la gestione dei beni confiscati alla criminalità organizzata. *Libera–Associazioni, nomi e numeri contro le mafie, Roma*, 60

Galletta, S. (2017) Law enforcement, municipal budgets and spillover effects: Evidence from a quasi-experiment in Italy. *Journal of Urban Economics* 101, pp. 90-105.

Garoupa, N. (2007). Optimal law enforcement and criminal organization *Journal of Economic Behavior and Organization* 63.3, pp. 461-474.

Gibbons, S. (2004). The costs of urban property crime. *Economic Journal* 114.

Gibbons, S. and Stephen Machin. (2008). Valuing school quality, better transport, and lower crime: Evidence from house prices. *Oxford Review of Economic Policy* 24.1, pp. 99-119.

Gibbons, S., Susana Mourato, and Guilherme M. Resende. (2014) The Amenity Value of English Nature: A Hedonic Price Approach. *Environmental and Resource Economics* 57, pp. 175-196.

Glaeser, E., Joseph Gyourko, and Raven E. Saks. (2005). Why have housing prices gone up? *American Economic Review* 95, pp. 329-333.

Guiso, L., Sapienza, P., and Zingales, L. (2004). The role of social capital in financial development. *American economic review*, *94*(3), 526-556.

Ihlanfeldt, K. and Tom Mayock. (2010). Panel data estimates of the effects of different types of crime on housing prices. *Regional Science and Urban Economics* 40.2-3, pp. 161-172.

Koster, H. R., van Ommeren, J., and Rietveld, P. (2012). Bombs, boundaries and buildings: A regression-discontinuity approach to measure costs of housing supply restrictions. *Regional Science and Urban Economics*, *42*(4), 631-641.

Koster, H. R., and Van Ommeren, J. (2019). Place-based policies and the housing market. *Review of Economics and Statistics*, *101*(3), 400-414.

Lee, P. and Alan Murie. (1999). Spatial and Social Divisions within British Cities: Beyond Residualisation. *Housing Studies* 14, pp. 625-640.

Linden, L. and Jonah E. Rockoff. (2008). Estimates of the Impact of Crime Risk on Property Values from Megan's Laws. *American Economic Review* 98:3, 1103-1127

Loberto, M. A. L., and Pangallo, M.. (2018). The potential of big housing data: an application to the Italian real-estate market. *Temi di discussione (Economic working papers) 1171. Bank of Italy.*

Manzoli, Elisabetta, and Sauro Mocetti (2019). The house price gradient: evidence from Italian cities. *Italian Economic Journal*: 1-25

Noonan, D. S., & Krupka, D. J. (2011). Making—or picking—winners: Evidence of internal and external price effects in historic preservation policies. *Real Estate Economics*, 39(2), 379-407.

Ooi, J. and Thao T.T. Le. (2013). The spillover effects of infill developments on local housing prices. *Regional Science and Urban Economics* 43.6, pp. 850-861.

Peri, Giovanni. (2004). Socio-Cultural Variables and Economic Success: Evidence from Italian Provinces 1951-1991. *The B.E. Journal of Macroeconomics* 4 pp. 1-36.

Pinotti, P. (2015). The Economic Costs of Organised Crime: Evidence from Southern Italy. *Economic Journal* 125.586 (2015), F203-F232.

Pinotti, P. and Piero Stanig. (2018) Sowing the Mafia: A Natural Experiment Bocconi, mimeo.

Rosenthal, S. S., Ross, S. L. (2015) Change and persistence in the economic status of neighborhoods and cities. In J. V. Henderson, G. Duranton and W. C. Strange (eds) *Handbook of Regional and Urban Economics*, Vol. 5, pp. 1047-1120. Elsevier.

Rossi-Hansberg, E., Sarte, P. D., and Owens III, R. (2010). Housing externalities. *Journal of political Economy*, *118*(3), 485-535.

Santiago, A., George C Galster, and Tatian, P.. (2001.) Assessing the property value impacts of the dispersed subsidy housing program in Denver. *Journal of Policy Analysis and Management* 20.1, pp. 65-88.

Schwartz, A.E., I. Ellen, I. Voivu, M. Schill (2006). The external effects of place-based subsidized housing. *Regional Science and Urban Economics* 36, pp. 679-707.

Storper, M. and A. J. Venables. (2004). Buzz: face-to-face contact and the urban economy. *Journal of Economic Geography* 4, pp. 351-370.

Transcrime. (2011, 2013, 2015, 2017). Gli investimenti delle mafie, rapporto di ricerca.

Trigilia, C. (2001). Social capital and local development. *European journal of social theory*, 4(4), 427-442.

Tables

Table 2. 1: OMI-level estimates

Log euro per m_2	(1)	(2)	(3)	(4)	(5)
Confiscation	0.0180	0.0179			0.0159
	(0.0145)	(0.0138)			(0.0186)
Re-allocation			0.0374***	0.0421**	0.0421**
			(0.0142)	(0.0187)	(0.0186)
Census controls	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Re-all. time	Any	No re-all. years	Any	10+	10+
Observations	255,995	253,080	253,562	251,779	251,779
R-squared	0.965	0.965	0.965	0.965	0.966

Notes. The table reports the estimation results for the difference-in-difference model testing the relationship between confiscation/re-allocation and property prices (see Section 2.4.1). The dependent variable is the average price per m_2 recorded for private properties in each OMI area. The confiscation dummy switches on in the year of confiscation until the time of reallocation. Consistently, the re-allocation dummy equals one from the year of re-allocation onwards. In columns (1) and (3), the analysis covers the whole sample. In column (2) re-allocation years are excluded from sample. In columns (4)-(5) only re-allocations taking 10 or more years from confiscation are included. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 2. 2: Sale point analysis – d=250

Log euro per m_2	Buffer radius: 250m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 year before re-allocation	0.00249	0.00211	0.00188	0.00301	0.00212		
	(0.00319)	(0.00315)	(0.00315)	(0.00322)	(0.00332)		
Re-allocation year	-0.00085	-0.00107	-0.00119	-2.57e-05	-0.00261		
	(0.00313)	(0.00312)	(0.00312)	(0.00282)	(0.00294)		
1 year after re-allocation	0.0083***	0.0079***	0.0076***	0.0081***	0.00556**		
	(0.00260)	(0.00255)	(0.00263)	(0.00254)	(0.00241)		
2 years after re-allocation	0.00299	0.00271	0.00253	0.00331	0.00130		
	(0.00260)	(0.00256)	(0.00259)	(0.00236)	(0.00265)		

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3 years after re-allocation	0.0071***	0.0064***	0.0063***	0.0064***	0.0058***		
	(0.00225)	(0.00220)	(0.00219)	(0.00181)	(0.00164)		
Re-allocation						0.00383**	0.00379**
						(0.00150)	(0.00151)
Confiscation							-0.00438
							(0.00276)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

Notes. The table reports the estimation results for hedonic analysis presented in Section 2.4.2. The dependent variable is the price recorded for each sale point *i* in year *t*. The main explanatory variables are the number of confiscation/reallocation events taking place *n* years before/after the transaction. Columns (1)-(5) report the effect of property re-allocation 1-3 years after the event. Housing prices differences recorded the same year or the year before make it possible to account for pre-treatment differences in housing prices. Columns (6) and (7) report the cumulative effect of confiscation and reallocation events on housing prices. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 2. 3: Sale point analysis – regional heterogeneity

	Campania, Calabria, Puglia, Sicily			Other Italian regions		
Dep. variable: Log euro per m2	100m	250m	500m	100m	250m	500m
	(1)	(2)	(3)	(4)	(5)	(6)
Re-allocation	0.00718**	0.00427**	0.00137	-0.00985	0.00431	-0.00210
	(0.00329)	(0.00190)	(0.00106)	(0.00948)	(0.00776)	(0.00776)
Confiscation	0.00302	0.00155	0.00155	0.00691	-0.00604	-0.00833
	(0.00290)	(0.00185)	(0.00185)	(0.0340)	(0.0115)	(0.0068)

Structural controls	✓	✓	✓	✓	✓	✓
Building controls	✓	✓	✓	✓	✓	✓
Amenity controls	✓	✓	✓	✓	✓	✓
Socio-econ. controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓	✓	✓
Observations	11,891	11,891	11,891	40,015	40,015	40,015
R-squared	0.719	0.719	0.719	0.787	0.787	0.787

Notes. The table reports the estimation results for hedonic analysis presented in Section 2.4.2. The dependent variable is the price recorded for each sale point *i* in year *t*. The main explanatory variables are the number of confiscation/reallocation events taking place *n* years before/after the transaction. Columns (1)-(3) report the effect of property re-allocation 1-3 years after confiscation/re-allocation events in the regions where mafia organisations are more rooted. Column (4)-(6) report the estimates for the remaining territory. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 2. 4: Sale point analysis – local deprivation

Log euro per m^2	Buffer: 250m			
	Unemployment		Bad real estate conditions	
	High (>75th perc.)	Low (<75th perc.)	High (>75th perc.)	Low (<75th perc.)

	(1)	(2)	(3)	(4)
Re-allocation	0.00385**	0.00185	0.00519***	0.00270
	(0.00181)	(0.00181)	(0.00158)	(0.00353)
Confiscation	-0.000690	0.00184	-0.00354	-0.0176
	(0.00285)	(0.00674)	(0.00288)	(0.0324)
Structural / building / amenity controls	✓	✓	✓	✓
Socio-econ. controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓
Observations	7,028	44,878	14,836	37,070
R-squared	0.601	0.769	0.794	0.772

Notes. The table reports the estimation results for hedonic analysis presented in Section 2.4.2. The dependent variable is the price recorded for each sale point *i* in year *t*. The main explanatory variables are the number of confiscation/reallocation events taking place *n* years before/after the transaction. Columns (1)-(3) report the effect of property re-allocation 1-3 years after confiscation/re-allocation events took place. The model is estimated using different samples, based on two proxies for local deprivation. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 2. 5: Street-level analysis: number of Mafia families

Dependent variable: number of Mafia families	100 m buffer			200 m buffer		
	(1)	(2)	(3)	(4)	(5)	(6)

confiscation	0.311***	-0.0989	0.0703	0.570***	0.0696	0.166**
	(0.0664)	(0.0613)	(0.0647)	(0.0502)	(0.0603)	(0.0681)
re-allocation	-0.583***	-0.153***	-0.364***	-0.435***	-0.0964***	-0.210***
	(0.0444)	(0.0301)	(0.0380)	(0.0318)	(0.0207)	(0.0252)
Observations	84,174	84,162	9,036	84,174	84,162	20,748
R-squared	0.849	0.942	0.928	0.849	0.942	0.933

Notes. The table reports the estimation results for linear regression model presented in Section 2.5.4. The dependent variable is the number of camorra families recorded in each road. In columns (1), (2), (4) and (5) the sample covers all Naples roads, whereas in column (3) and (6) it is restricted only to roads with confiscations/re-allocations. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

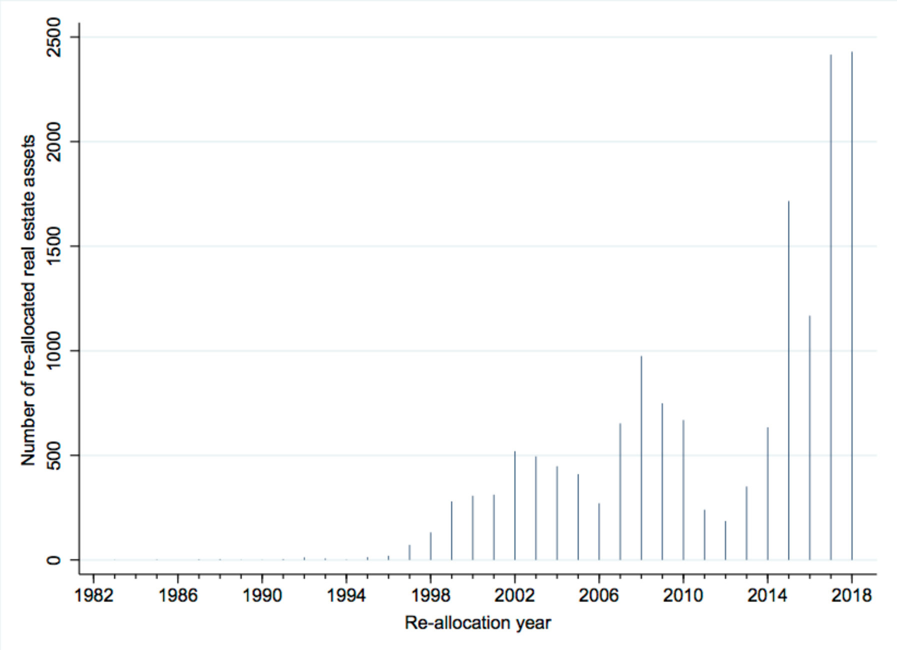
Table 2. 6: Street-level analysis: Mafia presence

Dependent variable: Mafia dummy	100 m buffer			200 m buffer		
	(1)	(2)	(3)	(4)	(5)	(6)
confiscation	0.0307***	0.00125	0.0187***	0.0386***	0.0208**	0.0362***
	(0.00370)	(0.00384)	(0.00692)	(0.00214)	(0.00822)	(0.0124)
re-allocation	-0.0182***	-0.0201***	-0.0135*	-0.0142***	-0.0152***	-0.00831*
	(0.00586)	(0.00538)	(0.00710)	(0.00437)	(0.00417)	(0.00483)
Observations	84,588	84,576	9,054	84,588	84,576	20,880
R-squared	0.874	0.944	0.936	0.874	0.944	0.935

Notes. The table reports the estimation results for linear regression model presented in Section 2.5.4. The dependent variable is a dummy equal to 1 if mafia activity is recorded in the street. In columns (1), (2), (4) and (5) the sample covers all Naples roads, whereas in column (3) and (6) it is restricted only to roads with confiscations/re-allocations. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

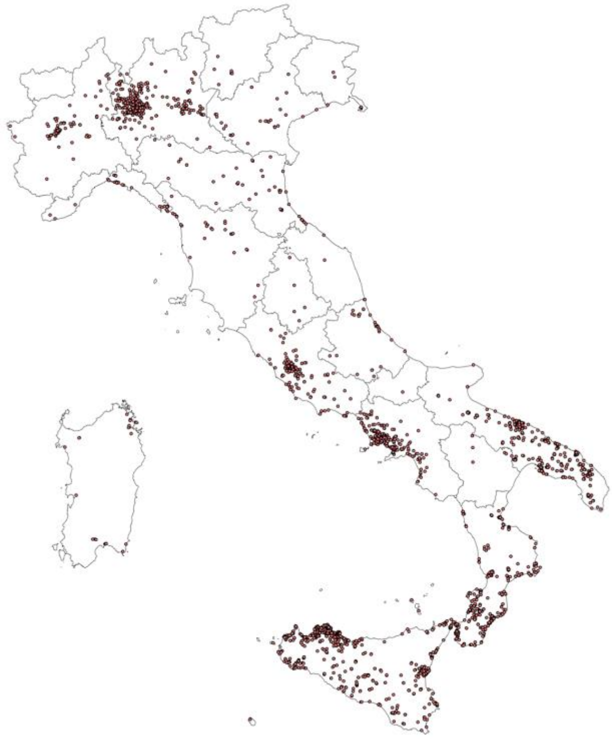
Figures

Figure 2. 1: Re-allocated real estate assets by year



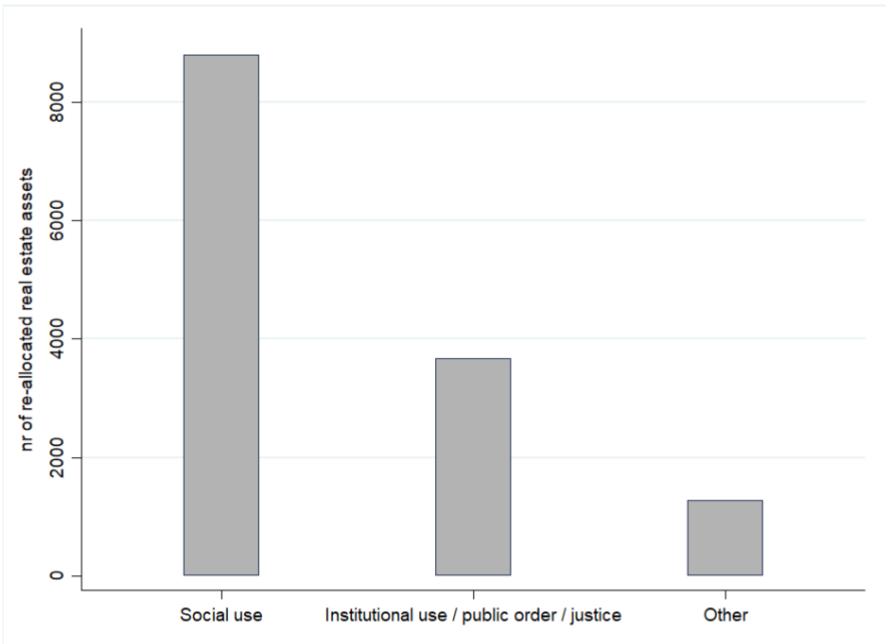
The figure shows the number of assets re-allocated by year, over the period 1982-2018.

Figure 2. 2: Re-allocations in Italy



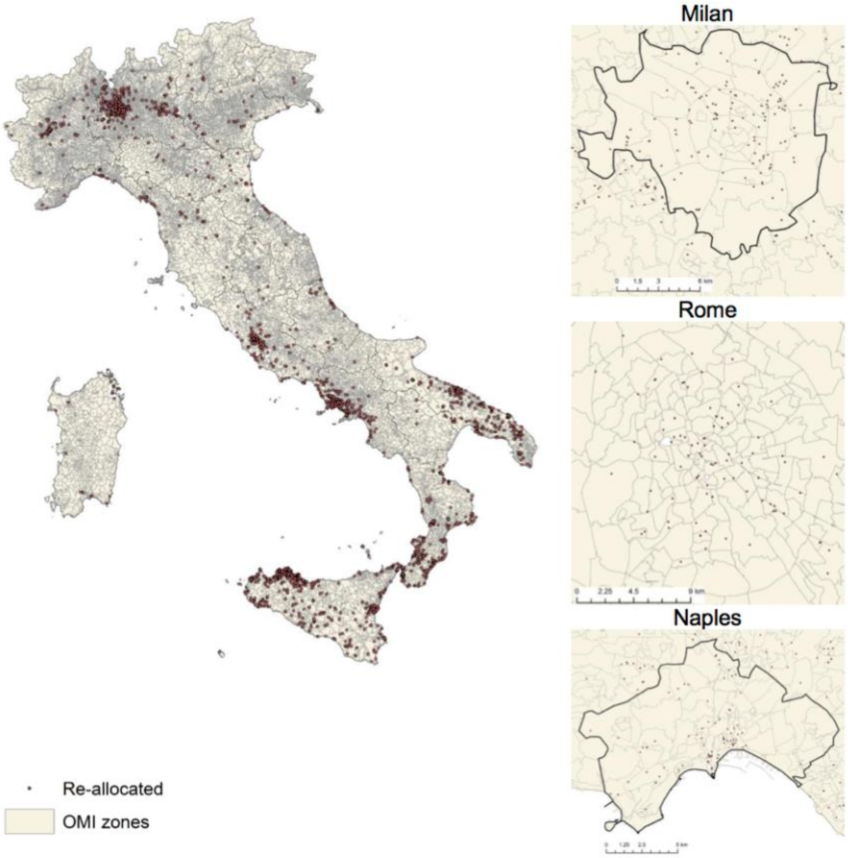
The figure shows the geographical location of confiscated assets across the Italian territory

Figure 2. 3: Re-allocation types



The figure shows the distribution of re-allocated assets by broader category.

Figure 2. 4: : OMI zones (Italy, Milan, Rome, Naples)

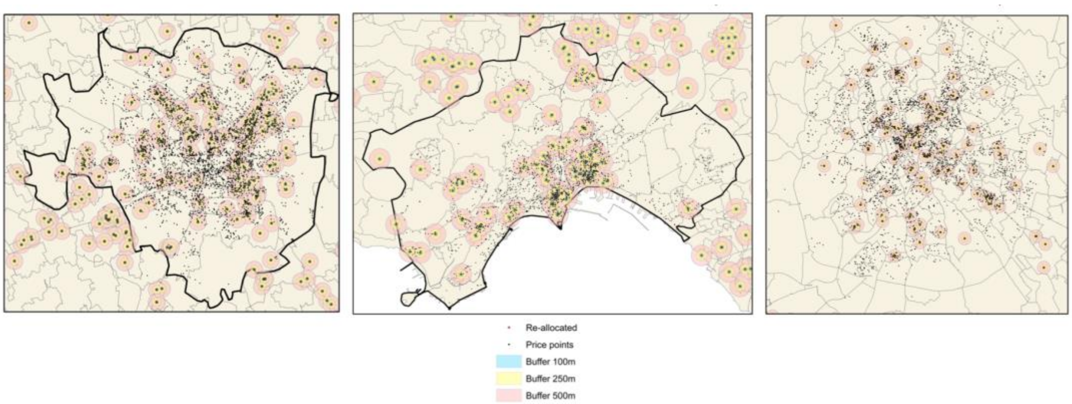


The figure shows re-allocated assets and OMI zones for the whole Italian territory and, in detail, for the three largest cities

Figure 2. 5: : Sale points in Italian cities

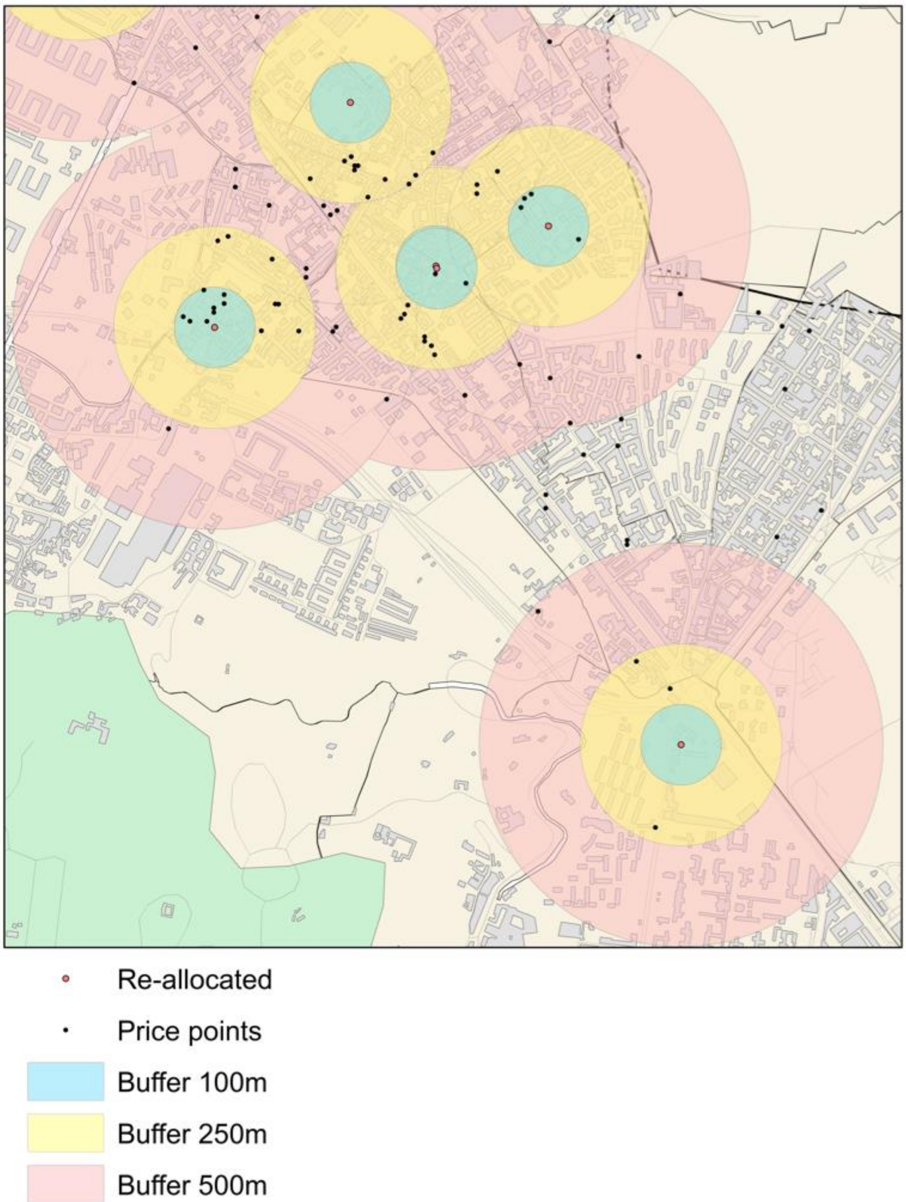
The figure shows the distribution of sale points across the 55 main Italian cities.

Figure 2. 6: : Sale points in major Italian cities



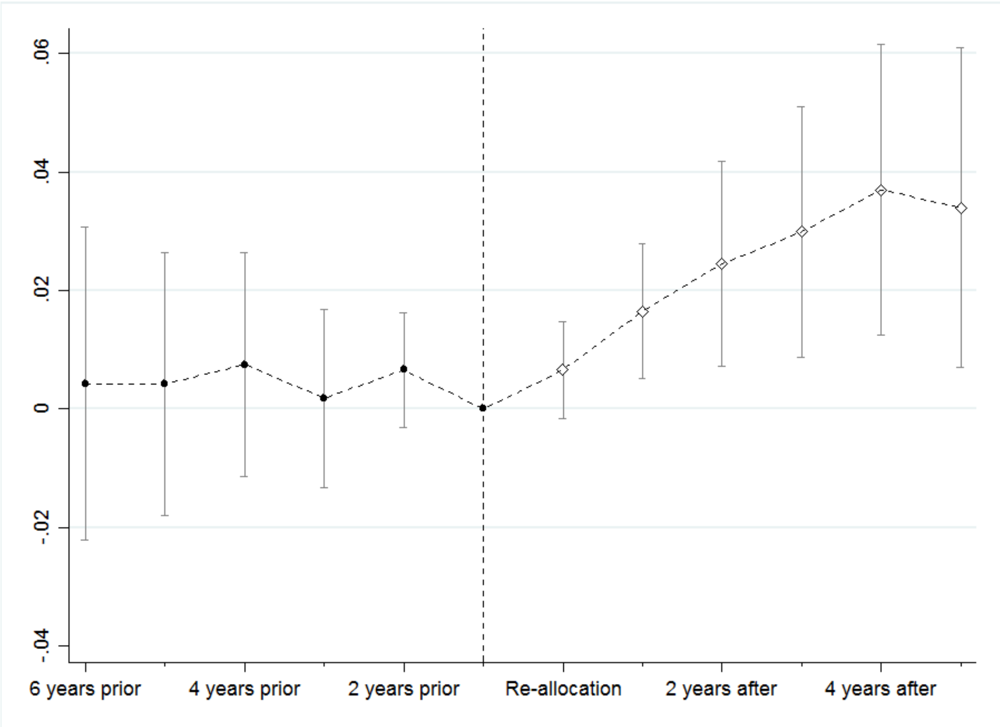
The figure shows 100m, 250m and 500m buffers around each sale point recorded in the three main Italian cities

Figure 2. 7: Buffer zones



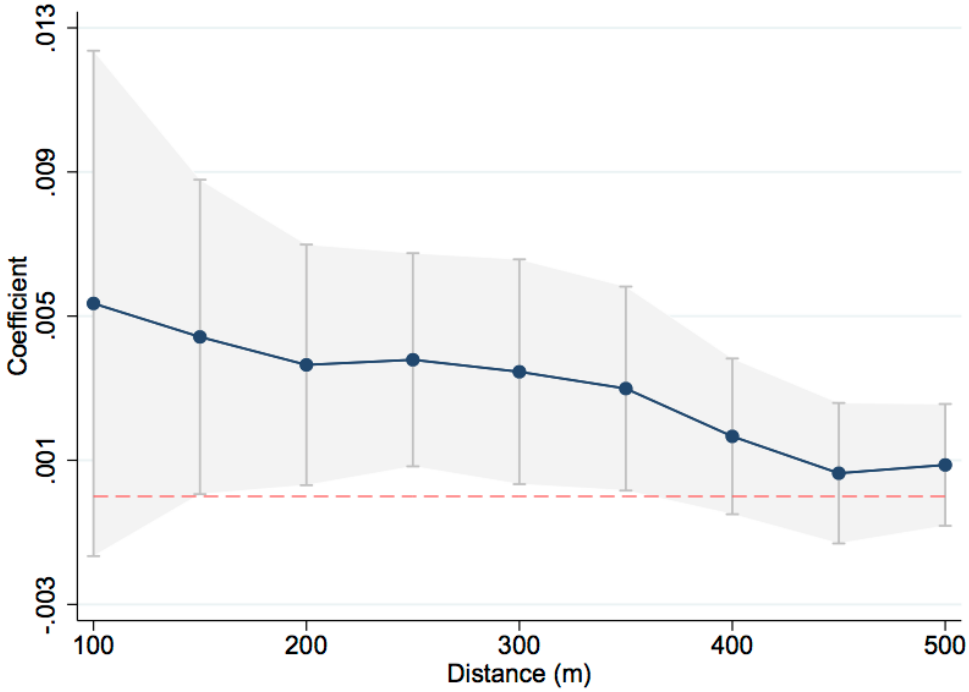
The figure provides a detailed representation of our methodology. Red dots represent re-allocated assets, black dots are sale points and blue, yellow and red areas represent, respectively the 100m, 250m and 500m buffer measured around each re-allocation. The point sales that in a given year fall inside a certain buffer *d* are said to be treated at distance *d*.

Figure 2. 8: Event study – re-allocation



The figure reports coefficients and confidence intervals for the event study conducted using OMI-level data.

Figure 2. 9: : Sale point analysis – distance decay



The figure reports coefficients and confidence intervals estimated in the hedonic specification. The figure allows to appreciate spatial decay characterising the cumulative treatment.

Figure 2. 10: Mafia families in Naples, 2013

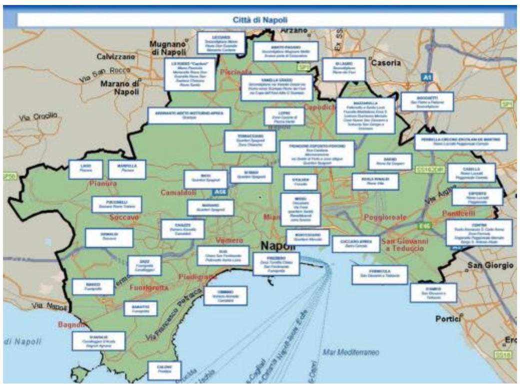
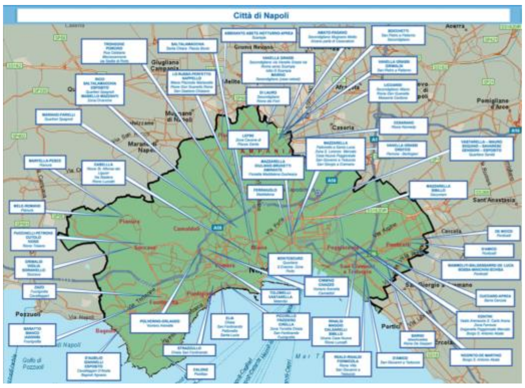
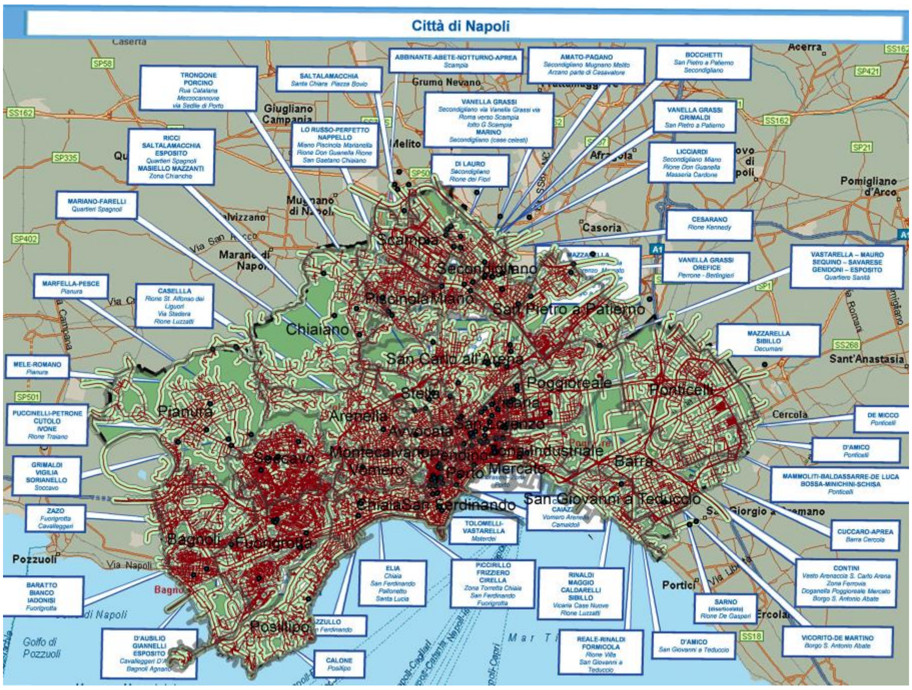


Figure 2. 11: Mafia families in Naples, 2018



The figure retrieved from Transcrime (2018) shows the spatial distribution of mafia families in Naples in 2013 and 2018

Figure 2. 12: Street-level dataset



The figure shows the Naples road network and the buffer constructed within 100m from both side of each road

Appendix

Table A2. 1: Timing of re-allocations

	Years between confiscation and re-allocation					
	0-1	2-3	4-5	6-7	8-9	10+
Number of re-allocated real estate properties	83	603	1,684	2,830	2,585	7,913
% of total re-allocated	0.5	3.8	10.7	18.0	16.5	50.4

Source: own elaboration with ANBSC data.

Table A2. 2: Re-allocation and local area characteristics

Dep. variable: Re-allocation	Local area characteristics: Ln pop	Illiterate pop	Unemployed	Rented pop	Buildings bad conditions
	(1)	(2)	(3)	(4)	(5)
	-0.0153*	0.00851	0.01758**	0.00695***	0.00441**
	(0.00859)	(0.00674)	(0.00710)	(0.00229)	(0.00182)
Observations	123,718	123,718	123,718	123,718	123,648
R-squared	0.001	0.001	0.007	0.017	0.002
	-0.000189	0.000228	0.000092	6.53e-05	-0.00337
	(0.000682)	(0.000369)	(0.000250)	(6.36e-05)	(0.00660)
OMI FE	✓	✓	✓	✓	✓
Observations	121,174	121,174	121,174	121,174	121,107
R-squared	0.913	0.913	0.913	0.913	0.913

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Re-allocation dummy. Local area conditions: Log population, percentage of residents with tertiary education, percentage of illiterate population, percentage of unemployed, percentage of foreigners, Buildings being occupied and used as percentage of total in local area, buildings in excellent conditions as percentage of total in local area, buildings in bad conditions as percentage of total in local area.

Table A2. 3: Local governments and re-allocation duration

	Italy local Governments 1998-2017		Re-allocations 1998-2017		Re-allocations timing: 0-9 years		Re-allocations timing: 10+ years	
	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
Party colour	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Right	5,886	14.3	2,436	26.9	1,256	27.9	1,777	39.2
Centre	5,158	12.6	595	6.6	305	6.8	290	6.4

Left	9,950	24.3	3,359	37.2	1,582	35.2	1,180	26.1
5Star	425	1.1	290	3.2	49	1.1	241	5.3
Civic list	23,664	57.7	2,280	25.3	1,332	29.7	948	20.9
Dissolved	274	0.7	300	3.3	202	4.5	98	2.1

Party colour: ideological leaning/party type of municipal governments during 1998-2017 in Italy. Civic lists: electoral lists/parties different from national parties, often created ad hoc for local elections. Right, Centre and Left include civic lists of that political colour. Civic list includes both ideologically identifiable lists and non-identifiable lists. Dissolved: municipal governments dissolved for any reason, such as collusion/corruption, financial disarray, vote of no confidence.

Table A2. 4: Re-allocation and local area characteristics

	Local area characteristics					Re-allocated building characteristics			
Dep. variable: Re-allocation timing	Ln pop	Illiterate pop	Unemployed	Rented pop	Buildings bad conditions	Social use	Institutional	Residential buildings	Terrains
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6.23e-06	0.0274	0.429***	0.0460	0.0746	-1.967***	2.440**	-0.269	-0.386
	(0.306)	(0.102)	(0.105)	(0.0342)	(0.0732)	(0.652)	(1.023)	(0.493)	(0.540)
Re-allocation year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,999	5,999	5,999	5,999	5,999	8,969	8,969	8,969	8,969
R-squared	0.005	0.005	0.006	0.005	0.006	0.009	0.009	0.007	0.007
	-0.284	0.0915	0.403	-0.0105	-0.0140	-1.862	1.883	-0.202	-2.458
	(0.531)	(0.168)	(0.402)	(0.0647)	(0.120)	(1.669)	(2.211)	(0.318)	(2.630)
Re-allocation year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,593	5,593	5,593	5,593	5,579	8,438	8,438	8,438	8,438
R-squared	0.078	0.078	0.078	0.078	0.077	0.089	0.089	0.089	0.089

Notes. The table illustrates the relation between the length of re-allocation procedure and characteristics of the area where the confiscation took place and of the asset. . Independent variable: columns (1)-(5): local area conditions. Log population, percentage of residents with tertiary education, percentage of illiterate population, percentage of unemployed, percentage of families being rented, buildings in bad conditions as percentage of total in local area. Columns (6)-(9): re-allocated building characteristics (dummy variables). Re-allocated for social use, re-allocated for institutional use, residential buildings, terrains. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A2. 5: Property characteristics

Type of data	Variables
Identifiers	Unique ad identifier, date in which the ad was created in the database, date in which the ad was removed from the database, date in which one of the characteristics of the ad was modified for the last time

Numerical	Price, floor area, rooms, bathrooms, year built
Categorical	Property type, kitchen type, heating type, maintenance status, floor, air conditioning, energy class
Type of building	Elevator, garage/parking spot, building category
Geographical	Longitude, Latitude, address
Temporal	Ad posted, ad removed, ad modified
Contractual	Foreclosure auction
Textual	Description

The table illustrates the main variable types available in the hedonic dataset

Table A2. 6: Descriptive statistics: treatment variables

Variable	Obs	Mean	Std. Dev.
OMI zones:			
Price €/m2	262,740	1188.5	778.9
Re-allocation	388,884	0.0166	0.128
Confiscation	388,884	0.0134	0.115
Sale points:			
Price €/m2	52,651	2415.3	1525.3
Re-allocation	52,651	0.166	1.269
Confiscation	52,651	0.0391	0.721
Re-allocation year	52,651	0.0487	0.608
1 year after re-allocation	52,651	0.0521	0.615
2 years after re-allocation	52,651	0.0339	0.594
3 years after re-allocation	52,651	0.0169	0.286
4 years after re-allocation	52,651	0.0142	0.197

The table reports descriptive statistics for the variables of interest.

Table A2. 7: Descriptive statistics: sale point characteristics

Variable	Mean	Std. Dev.
Distance to green area	6,647.6	4,305.6
Distance to beach max 20km	172,000	335,000
Distance to city viewpoint 1km	19,962.3	10,809.2

Distance to a University	50,317.5	27,780.2
Distance to bus, tram or metro	3,081.6	755.6
Distance to Intercity transport, railway	6,017.8	1,750.8
Distance to airport	17,593.4	17,172.7
Distance to commercial centre	25,858.5	14,489.2
Distance to church	729.5	406.9
Distance to state schools	6,896.7	994.2
Noise - within 500m of a highway	0.23	0.06
Dummy industrial area	0.16	0.03
Distance to factory	5,859.9	2,665.2
Distance to construction site	19,820.4	9,124.5
Month of offer	3.51	5.00
Lift dummy	0.49	0.41
Building height	8.04	14.05
Typology of building	1.24	2.62
Area of building	1,141.1	538.4
Average typology of building in street	0.66	2.71
Property up for auction	0.14	0.02
Type of property	0.71	4.02
Number of rooms	1.30	2.80
Number of bathrooms	0.69	1.51
Type of kitchen	0.70	1.46
Floor number	2.61	2.01
Parking with property	0.47	0.33
Periods year built	2.01	2.49
Property condition	1.08	2.19
Property heating type	0.73	0.93
Air conditioning	0.44	0.27
Energy Efficiency	0.83	0.87

The table reports descriptive statistics for the sale-point-level variables used in the analysis.

Table A2. 8: Descriptive Statistics: Census area characteristics

Variable	Obs	Mean	Std. Dev.

Population	123,718	341.7	265.8
% Illiterate population	123,718	0.94	1.43
% Unemployed	123,718	3.24	1.82
% Rented families	123,718	8.30	7.20
% Buildings bad conditions	123,648	1.15	4.28

The table reports descriptive statistics for census-area-level variables used in the analysis.

Table A2. 9: Re-allocation and electoral turnout

	Dep. variable: Re-allocation		*Dep. variable:* Re-allocation timing	
	(1)	(2)	(3)	(4)
Turnout	-0.168***	0.0115	-17.46***	-0.984
	(0.00935)	(0.0162)	(1.857)	(5.306)
OMI FE		✓		✓
Observations	26,898	26,898	633	633
R-squared	0.003	0.044	0.123	0.445

Notes. The table illustrates the relation between re-allocation events, duration of the re-allocation procedure and local turnout. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

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Table A2. 10: Sale point analysis – d=150

Log euro per m2	Buffer radius: 150m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 year before re-allocation	-0.000447	-0.00114	-0.00158	0.000269	-0.000654		
	(0.00531)	(0.00548)	(0.00543)	(0.00581)	(0.00569)		
Re-allocation year	-0.00376	-0.00439	-0.00475	-0.00263	-0.00556		
	(0.00600)	(0.00580)	(0.00580)	(0.00522)	(0.00542)		
1 year after re-allocation	0.00754	0.00692	0.00628	0.00756*	0.00574		
	(0.00514)	(0.00495)	(0.00499)	(0.00464)	(0.00398)		
2 years after re-allocation	0.00449	0.00400	0.00390	0.00433	0.00224		
	(0.00492)	(0.00484)	(0.00488)	(0.00431)	(0.00443)		
3 years after re-allocation	0.00549*	0.00503*	0.00487*	0.00494**	0.00549**		
	(0.00303)	(0.00294)	(0.00288)	(0.00222)	(0.00219)		
Re-allocation						0.00439**	0.00442**
						(0.00220)	(0.00222)
Confiscation							-0.00544
							(0.00376)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

Notes. The table reports the estimation results for hedonic analysis presented in Section 2.4.2. Columns (1)-(5) report the effect of property re-allocation taking place within 150m from the sale point. Housing prices differences recorded the same year or the year before make it possible to account for pre-treatment differences in housing prices. Columns (6) and (7) report the cumulative effect of confiscation and reallocation events on housing prices. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A2. 11: Sale point analysis – d=500

Log euro per m2	Buffer radius: 500m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 year before re-allocation	0.00220	0.00215	0.00194	0.00248	0.00115		
	(0.00175)	(0.00172)	(0.00173)	(0.00176)	(0.00203)		
Re-allocation year	0.00202	0.00212	0.00198	0.00235*	0.000879		
	(0.00139)	(0.00134)	(0.00133)	(0.00126)	(0.00130)		
1 year after re-allocation	0.00311**	0.00277**	0.00254*	0.00314**	0.00139		
	(0.00146)	(0.00140)	(0.00145)	(0.00140)	(0.00117)		
2 years after re-allocation	0.00180	0.00186	0.00174	0.00229**	8.38e-05		
	(0.00119)	(0.00116)	(0.00118)	(0.00104)	(0.00110)		
3 years after re-allocation	0.00254*	0.00241*	0.00226*	0.00312***	0.00307***		
	(0.00137)	(0.00133)	(0.00132)	(0.00114)	(0.00113)		
Re-allocation						0.000954	0.000872
						(0.00086)	(0.00086)
Confiscation							-0.0035**
							(0.00151)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

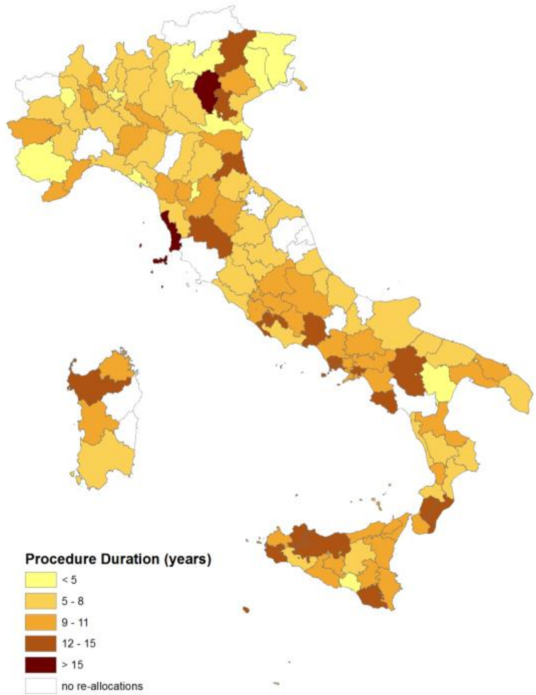
Notes. The table reports the estimation results for hedonic analysis presented in Section 2.4.2. Columns (1)-(5) report the effect of property re-allocation taking place within 500m from the sale poin. Housing prices differences recorded the same year or the year before make it possible to account for pre-treatment differences in housing prices. Columns (6) and (7) report the cumulative effect of confiscation and reallocation events on housing prices. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A2. 12: Sale point analysis controlling for buffer zone

Dep. variable: Log euro per m2	100m	200m	300m	400m	500m
	(1)	(2)	(3)	(4)	(5)
Buffer zone	-0.00762	-0.0188	-0.0192	-0.0301*	-0.0328*
	(0.0112)	(0.0169)	(0.0149)	(0.0172)	(0.0175)
Re-allocation	0.00706**	0.00402**	0.00335**	0.00222**	0.00175*
	(0.00342)	(0.00171)	(0.00153)	(0.00110)	(0.00088)
Structural controls	✓	✓	✓	✓	✓
Building controls	✓	✓	✓	✓	✓
Amenity controls	✓	✓	✓	✓	✓
Socio-econ. controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓	✓
Observations	51,906	51,906	51,906	51,906	51,906
R-squared	0.784	0.784	0.784	0.784	0.784

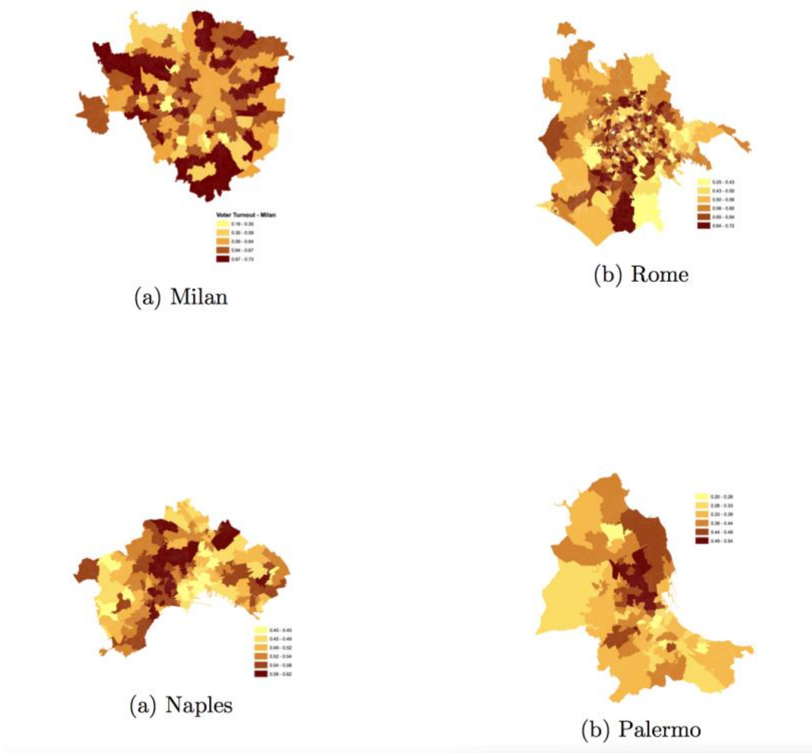
Notes In this table we test the robustness of these results by including in the model a control for the buffer zone, controlling for time-invariant characteristics located at a distance d from the sale point. Robust standard errors are clustered at the municipality level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Figure A2. 1: Re-allocation duration by Court



The figure shows the average time required for local cohorts to re-allocate confiscated mafia assets

Figure A2. 2: Polling station areas



The figures report the average voter turnout in the European elections by polling station area in four Italian cities